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HOW DOES SPACE AFFECT THE ALLOCATION OF THE EU RURAL DEVELOPMENT POLICY'S EXPENDITURE?

AN ECONOMETRIC ASSESSMENT

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HOW DOES SPACE AFFECT THE ALLOCATION OF THE EU RURAL DEVELOPMENT POLICY'S EXPENDITURE?

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di Beatrice Camaioni[2], Roberto Esposti[1], Francesco Pagliacci[1], Franco Sotte[1]

Abstract

This paper focuses on the main drivers of the distribution of the Rural Development Policy's expenditure throughout the EU. Ex-post funds distribution across EU NUTS3 regions is considered. Three effects are admitted as major drivers: the "country effect"; the "rural effect" (i.e., the more rural a region the larger the amount of support it is expected to receive); the "pure spatial effect" (i.e. the influence of bordering regions and, in particular, of their degree of rurality). These effects are estimated adopting alternative spatial model specifications: spatial Durbin model, SEM and SAR model. Results differ across alternative specifications and definitions of rurality, but the prevalent evidence suggests that rurality matters in a counterintuitive direction, while also neighbouring regions play a role.

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1. Introduction: the Objective of the Study

This paper is aimed at assessing the relevance of the space in influencing the allocation of the Rural Development Policy (RDP) expenditure at "local" level, that is, across about 1300 EU NUTS3 regions. Three different effects are here considered as major drivers of this spatial allocation. First, a *country effect* can be observed: each EU Member State shows different intensities of RDP expenditure as effect of the well known differentials in the rural support across EU countries. Then, a *rural effect* is expected to capture the fact that, at least in principle, the more rural a given region the larger the amount of RDP support it is expected to receive. However, this effect depends on what is meant with "rural regions" and, therefore, it may vary according to alternative definitions of rurality. Lastly, a *pure spatial effect* captures the idea that, given the country and the degree of rurality, the amount of support received by a region can be also influenced by the amount of support received by the neighbouring regions and, consequently, also by their degree of rurality. The presence of this latter effect requires a further justification.

Working at the maximum disaggregated territorial level (NUTS3), adopting alternative and more comprehensive definitions of rurality, explicitly modelling spatial dependence, represent the main original aspects of the present study. Evidently, the research objective is not new as previous studies already investigated the territorial allocation of the EU RDP funds (Shucksmith et al., 2005; Crescenzi et al., 2011). However, these works only considered NUTS2 level, at maximum, and the allocation of RDP support did not actually concern the real expenditure but only the *ex ante* allocation of funds (as established by political decisions taken at the EU and national levels), or the reconstruction of the real expenditure based on some sample observations. Moreover, these investigations limit the attention to the EU15 and not to the current entire extension of the EU. Therefore, what is new in the present analysis is higher level of territorial disaggregation (NUTS3 level) and coverage (EU27), and nature of the expenditure data. These latter are the total real payments as registered *ex post* by the EU bureaus aggregating individual beneficiaries at NUTS3 level.

It can be argued that NUTS3 territorial scale might be not appropriate for this kind of policy analysis, that is, for investigating distribution of policies whose *ex ante* allocation decisions are taken at an higher territorial and institutional level (EU, NUTS0 or NUTS1 level). In fact, this is the main reason why working at NUTS3 level with real expenditure data may be insightful with respect to previous works and, eventually, the main argument supporting the presence of a pure spatial effect in funds' spatial distribution. The expenditure observed at this territorial scale does not only depend on some top-down political decisions, observable *ex ante*, but also on the bottom-up capacity of territories to attract and really use these funds, and this actual delivery at a lower territorial level can only be observed *ex post*. Such kind of policy evaluation, therefore, does not only concern political decisions but has also to do with the real implementation of policies across space. Of this implementation, the underlying higher-level political decision is just part of the story. The other part is given by the capacity and the specific features of individual territories (NUTS3 regions) eventually affecting the expenditure they really receive. In this respect, space (i.e., the neighbouring regions) matters.

According to this general framework, the present paper analyses the spatial allocation of the RDP funds by estimating the three above-mentioned effects throughout the specification of a sequence of econometric models. Since the basic assumption is that space matters, the paper moves from a generic OLS model to models where spatial dependence (or correlation) is made explicit in different forms. An appropriate specification testing procedure allows selecting among the different forms.

The work is organised as follows. Section 2 provides some detailed information on RDP expenditure data. Moreover, some alternative measures of rurality are suggested, in order to properly assess the rural effect. Section 3 describes the econometric models: i) the generic *OLS model* that does not take into account any spatial effect; ii) the *SLX model*, accounting for the spatially-lagged independent variables (in particular the spatial lag of the rural effect);

iii) the *SEM* (*Spatial Error Model*), specifying a spatially correlated error term; iv) the *SAR* (*Spatial AutoRegressive*) model, containing the spatially lagged dependent variable; v) the *SDM* (*Spatial Durbin Model*) containing both a spatially lagged dependent variable and spatially lagged independent variables. Section 4 illustrates and discusses the main estimation results. Section 5 concludes the paper, by suggesting some policy implications of the analysis together with possible directions of future research in this field.

2. Data

2.1. RDP Expenditure

The Rural Development Policy (RDP) is the second pillar of the Common Agricultural Policy (CAP) and is funded by the European Agricultural Fund for Rural Development (EAFRD). It aims at supporting EU rural areas as a vital part of the EU economy and society. In spite of some major weaknesses, those regions have been facing new opportunities and challenges within the progressive transformation of the developed industrial economies (Mantino, 2005; OECD, 2006; Copus et al., 2008; Esposti, 2011; Sotte et al., 2012). In the 2007-2013 programming period under consideration here, the EU RDP aims at: i) improving the competitiveness of the agricultural and forestry sector (economic restructuring of rural areas); ii) enhancing the sustainable management of natural resources and helping regions in meeting future economic and environmental challenges; iii) improving the quality of life in rural areas (throughout the increasing diversification of the rural economies).

In pursuing these general objectives, EAFRD expenditure does not show a homogenous spatial allocation. Here, data on total EAFRD actual expenditure have been collected at NUTS3 level according to the NUTS2006 classification (1303 regions) for years 2007 to 2011.[1]

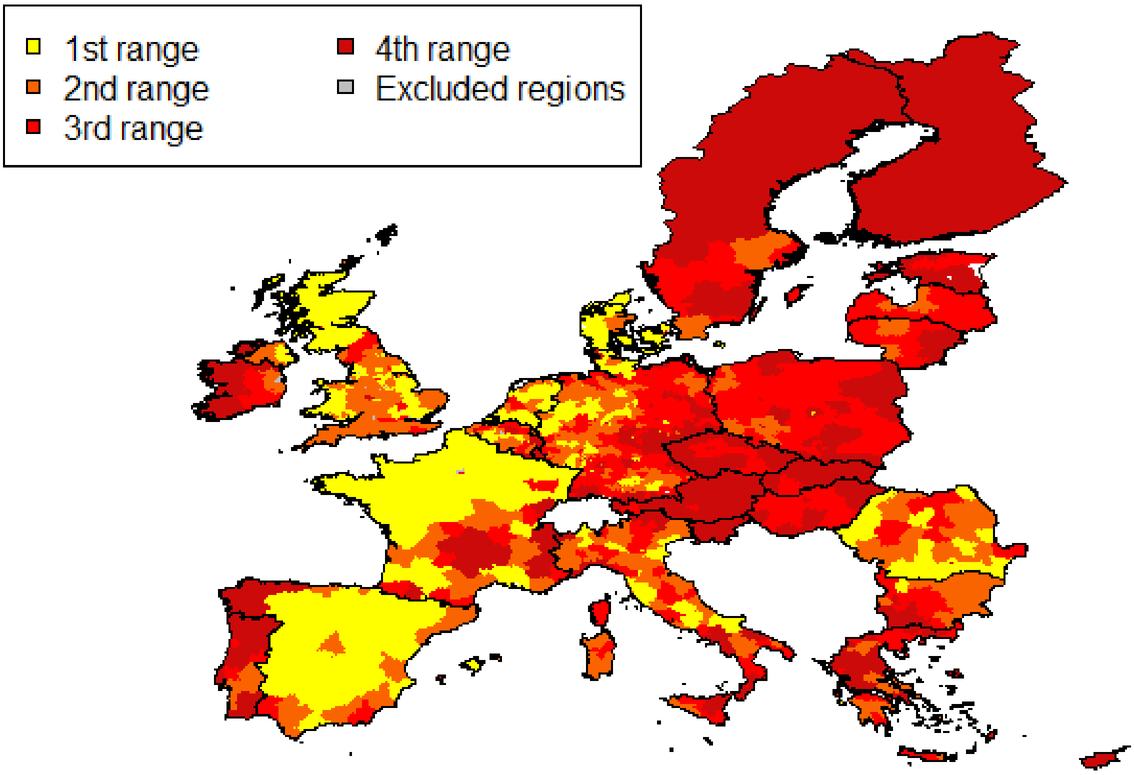
[1] The ambition here would be to cover the whole 2007-2013 programming period. However, *ex-post* NUTS3 expenditure data are currently updated only to 2011. Moreover, it is worth reminding that the expenditure of two subsequent periods may overlap. Therefore, the observed expenditure in the early years (2007 and 2008) could still refer to the previous

At this geographical scale, these data expenditure are obtained from real payments as registered *ex post* by the EU bureaus aggregating individual beneficiaries. By themselves, these expenditure data do not allow a proper comparison of RDP support across regions due to their largely different size. Therefore, the analysis on fund allocation is here performed by means of three indexes of expenditure intensity: RDP expenditure per unit of Utilized Agricultural Area in ha (€/UAA); RDP expenditure per agricultural Annual Working Unit (€/AWU); RDP expenditure per thousand Euros of agricultural Gross Value Added (€/.000 €).[2] These indexes confirm the heterogeneous spatial allocation of the RDP expenditures. Figure 1 shows the spatial quartile distribution (ranges) for RDP intensity per unit of Utilised Agricultural Area (UAA) at NUTS3 level throughout the EU-27. Figure 2 analogously displays the quartiles (ranges) of RDP intensity per agricultural Annual Work Unit (AWU). Figure 3 shows the spatial quartile distribution for RDP intensity per thousand Euros of agricultural GVA.

programming period while, at the same time, expenditure still referring to programming period 2007-2013 but actually made in 2014 or 2015 would remain unobserved even if 2012 and 2013 data were available. The same argument, the distribution over time of the expenditure for a given programming period, explains why having five years of observation (2007-2011) of 1303 regional expenditure does not constitute a panel dataset. Within a given programming period, the year-by-year expenditure is not informative on the spatial allocation of funds as it strongly depends on how each national/regional Rural Development Programme peculiarly uses and allocates the initial budget across years, areas and measures. In fact, it is not correct to consider annual expenditure levels as independent observations: some regions could actually spend a larger portion of the total amount of their funds in the first years of each programming period, while others may postpone payments at the very end of the programming period. Therefore, for what is of interest here (the allocation across space) the only longitudinal observations (therefore, panel dataset) could be those referring to subsequent programming periods. This is evidently unfeasible here.

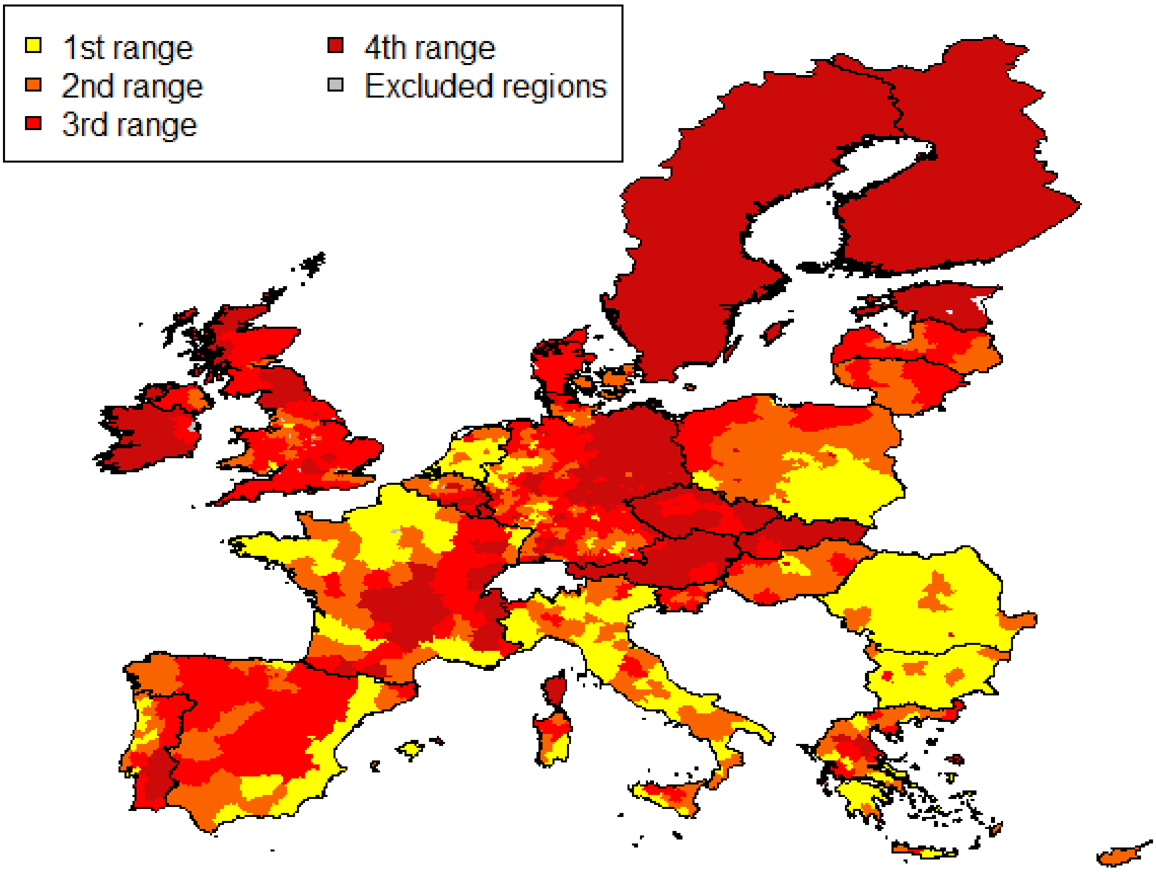
[2] Data on utilized agricultural areas (UAA) and annual work units (AWU) are collected from the Eurostat Farm Structure Survey (2007). Data on agricultural GVA are taken from Eurostat National Accounts (the average value for years 2007 to 2010 is considered).

Figure 1 – Spatial quartile distribution for Rural Development Policy intensity per unit of Utilised Agricultural Area (€/UAA) at NUTS3 level (2007-2011 values) (1st range = lower intensity)



The emerging territorial distribution can be attributed to some major differences across EU regions and, in particular, to their own land-use characteristics (e.g., the presence of woodlands and forests) and sector-based characteristics (e.g., the relevance of the agricultural sector within the local economy), but it also evidently depends on geographical characteristics, that is, the country they belong to and, maybe, the surrounding space (regions). In any case, the combination of all these factors generates a complex picture. For instance, the RDP expenditure intensity per unit of UAA is particularly low in both the plain regions of Northern France and of Spain. Conversely, the RDP expenditure intensity per agricultural GVA (in thousand €) is particularly high in the regions of Eastern European Countries due to their lower agricultural GVA values.

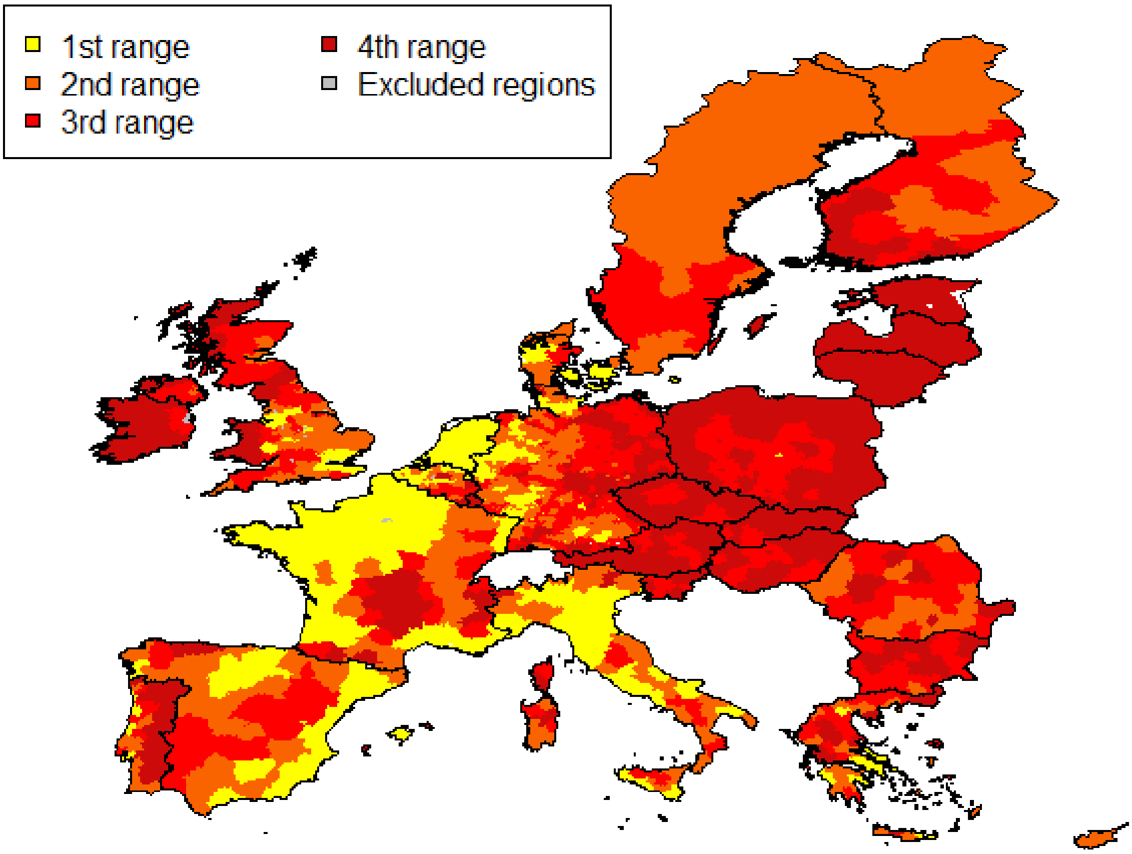
Figure 2 – Spatial quartile distribution for Rural Development Policy intensity per agricultural Annual Work Unit (€/AWU) at NUTS3 level (2007-2011 values) (1st range = lower intensity)



Moreover, by analysing in detail the RDP expenditure intensity at NUTS3 level, some outliers can be detected: they mainly refer to those urban areas where UAA and AWU are quite small but expenditure is still significant as several RDP beneficiaries are located in these regions. This implies "artificially" high levels of expenditure intensity. Thus, they have been dropped out from the original dataset. In particular, it has been decided to exclude those regions fulfilling at least one the following criteria: i) UAA ≤ 1000 ha.; ii) Agricultural AWU ≤ 10; iii) agricultural GVA ≤ 100 000 €. Accordingly, 30 NUTS3 regions (capital cities and other city regions, mainly located in the United Kingdom) have been excluded. Besides these 30 urban outliers, other 15 regions far from the European continent are regarded as outliers and therefore excluded (e.g., French *Departements d'outre-*

Mer, Spanish and Portuguese Atlantic Islands). Eventually, the number of total observations under investigation is 1258.

Figure 3 – Spatial quartile distribution for Rural Development Policy intensity per thousand Euros of agricultural GVA (€/.000 €) at NUTS3 level (2007-2011 values) (1st range = lower intensity)



2.2. Alternative Measures to Define Rurality

The most challenging issue in explaining RDP expenditure intensity as a combination of the three abovementioned effects consists in their proper identification. The *country effect* is straightforward as it just requires the introduction of dummy variables expressing the country to which any given region belongs. On the contrary, the *rural effect* requires a proper definition of how much rural a given region is; the *pure spatial effect* implies the specification of how neighbouring regions have an influence. This latter is an econometric issue and will be dealt with in next section.

In principle, the degree of rurality should be the prominent driver of the spatial allocation of RDP expenditure among regions. In practice, over the last two decades a wide literature has focused on defining and measuring the degree of rurality. However, a homogeneous and univocal definition distinguishing rural regions from urban ones is still lacking at international level (Montresor, 2002; Anania and Tenuta, 2008). For example, the EC does not provide any formal criterion to identify those areas where rural development policies are expected to be implemented: each Member State (or NUTS2 region) is autonomously in charge of defining its own rural areas. This is justified by the fact that wide differences in terms of demographic, socio-economic and environmental conditions still affect EU rural areas (European Commission, 2006; Hoggart et al., 1995; Copus et al., 2008). Also the lack of comparable statistics, at a disaggregated level, is usually considered as a substantial obstacle preventing a comprehensive definition of rurality (Bertolini et al., 2008; Bertolini and Montanari, 2009).

In spite of these major issues, some indicators are universally considered as valid criteria in order to indentify rural areas. Population density is among them. In this respect, the most widely cited urban-rural typologies are those proposed by the OECD (1994; 1996; 2006) and by the EC (Eurostat, 2010): both typologies follow a similar approach based on the population density and the presence of major urban areas. According to the OECD-Eurostat methodology, NUTS3 regions in the EU27 Member States are classified as *predominantly urban* (PU), *intermediate* (IR) and *predominantly rural* (PR) regions. Therefore, both population density by itself and the OECD-Eurostat methodologies are commonly used to define rural areas across Europe.

However, in post-industrial societies these dichotomous definitions of rural areas (mostly based on density) seem largely outdated (Sotte et al., 2012). The main reason is that they do not capture two fundamental characteristics of rurality within the EU. On the one hand, rurality expresses a combination of characteristics, and population density is just one of them. On the other hand, rurality being multidimensional, it is a heterogeneous trait depending on the specific geographic and socio-economic context. Rurality within highly-developed central macro-areas necessarily differs from rurality within an under-developed and highly peripheral context. The same OECD, and recently also the FAO, has opened a new research line in order to establish a qualified set of variables to more properly measure the extent of rurality also at the EU level (FAO-OECD Report, 2007; The Wye Group, 2007). Therefore, multidimensional approaches are increasingly suggested in defining rural and urban areas.

Following this idea, a comprehensive PeripheRurality Indicator (PRI) has been computed by Camaioni et al. (2013). This synthetic but continuous indicator is obtained by applying a principal component analysis (PCA) to a set of 24 variables, grouped in four different thematic areas capturing four different and complementary dimensions of rurality: 1. Socio-demographic characteristics (7 indicators), focusing on the demographic structure and on major demographic trends; 2. Structure of the economy (7 indicators), referring to the structural composition of the regional economy (share of agricultural activities, manufacturing sectors and services on total economy, per capita GDP…); 3. Land use characteristics (3 indicators), taking into account the presence of forests, agricultural areas and artificial areas; 4. Geographical features (7 indicators), referring to the accessibility of regions and their distance from major urban areas, that is, variables expressing the degree of peripherality or remoteness of the region (this explains the name of the synthetic indicator, *PeripheRurality*) (Camaioni et al., 2013).

Using data on these 24 variables at NUTS3 level, Camaioni et al. (2013) extracted five Principal Components (PCs) that were denominated as follows: PC1 – Economic and geographical centrality; PC2 – Demographic shrinking and ageing; PC3 – Manufacturing in rural areas with well performing labour market; PC4 – Land Use: forests vs. agricultural areas; PC5 – Urban dispersion. These PCs provide a first synthesis of the multidimensionality and heterogeneity of rurality within the EU27, but yet this synthesis is not enough to express the degree of rurality (thus, the *rural effect*) of a given region with an unique comprehensive variable. To achieve this, Camaioni et al. (2013) use these PCs to compute the PRI. Firstly, an ideal region characterized by extreme urban features is established. This European 'urban benchmark' is defined calculating, for each PC, the average score between the only two EU global Metropolitan Economic Growth Areas (MEGAs), Paris and London (ESPON, 2005). Secondly, the distance between any NUTS3 region and this urban benchmark is computed for all the PCs. The PRI of the *i*-th region is then computed as the following Euclidean distance (Camaioni et al., 2013):

$$PRI_i = \sqrt{\sum_p \left(x_{ip} - x_{ubp}\right)^2}\ ,\ \forall i \in N \tag{1}$$

where $N = 1, \ldots, n$ indicates the set of regions under consideration, x_{ip} represents the *i*-th region's score for the *p*-th PC and x_{ubp} represents the urban benchmark's score for the *p*-th PC. By construction, the greater the PRI the more rural and peripheral the *i*-th region is.

In order to take into account these possible measures of rurality, in the present analysis the rural effect will be alternatively expressed by the following indicators: Population density (the lower the density the more rural the region); Eurostat (2010) typologies (*Predominantly Rural, PR,* regions, *Intermediate, IR,* regions and *Predominantly Urban, PU,* regions); PRI (the greater the PRI, the more rural the region).

3. The Econometric Specifications

The main and original methodological contribution, here, actually concerns the identification and estimation of the *pure spatial effect*. It means to identify how space (i.e., the neighbouring units) affects, *ceteris paribus*, the amount of expenditure delivered to a given region. Making this role of the space explicit is essentially a specification problem.

3.1. *The OLS Model*

Let's start assuming that space does not matter. The first suggested model to test the main drivers in the allocation of the RDP support across EU NUTS3 regions is a simple Ordinary Least Squares (OLS) model. It does not take into account any specific spatial effect. The model can be expressed in the following form:

$$\mathbf{Y} = \mathbf{D}\boldsymbol{\beta} + \gamma\mathbf{X} + \boldsymbol{\varepsilon} \qquad (2)$$

where: **Y** is the (n x 1) vector, where n = 1288, indicating the RDP expenditure intensity (alternatively expressed per UAA, AWU, .000 €). **D** is the (n x 27) matrix of country dummies and $\boldsymbol{\beta}$ is the (27 x 1) vector or respective unknown parameters expressing the *country effect* and the constant term (see Table A1). Actually, to avoid perfect collinearity, one country dummy must be skipped (Austria is skipped in the present case).

X is, alternatively, a (n x 1) vector expressing the degree of rurality, that is, density (negatively related to rurality), PRI (positively related to rurality) or a (n x 2) matrix of dummies indicating urban-rural typologies (PR, IR, PU regions); γ is the respective unknown parameter indicating the *rural effect*. $\boldsymbol{\varepsilon}$ is a (n x 1) vector of i.i.d N~$(0,\sigma^2\mathbf{I})$ disturbance terms. Therefore, (2) implicitly assumes no spatial correlation across units (regions) and, consequently, excludes the presence of a *pure spatial effect*. One could argue that the degree of rurality and, therefore, the rural effect is itself the consequence of the RDP and its allocation across space. In other words, this argument suggests that there may be a problem of endogeneity in (2), the assumption $E(\mathbf{x}\boldsymbol{\varepsilon})=0$ being not necessarily valid. While, in principle, this argument may seem reasonable, all variables included in **X** can not be affected by **Y**, at least in the present case, as they all express structural features of the regions and pre-treatment (i.e., before the RDP expenditure) variables. This is definitely the case of population density but also of all variables expressed by the PRI composite indicator (see section 2.2). All these variables are observed in the 2006-2009 period (Camaioni et al., 2013) and their relative variation (i.e., the regional comparison) expresses very long-term adjustments and processes that can be in no case affected by the 2007-2011 RDP expenditure.[3]

3.2. *Testing for Spatial Autocorrelation: the Moran's I Statistics*

Model (2) and the consequent OLS estimation is not appropriate in case of spatially correlated disturbance terms, that is, whenever $E(\varepsilon_i \varepsilon_j) \neq 0,\ i, j \in N$. This evidently happens when there is spatial correlation in the observed dependent variables **Y** that is not fully taken into account by the independent variables, **D** and **X**. In order to test the presence of this spatial dependence we compute the global Moran's I statistics, a synthetic measure of spatial autocorrelation computed as follows (Moran, 1950; Cliff and Ord, 1981):

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2}, \forall i, j \in N$$

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\,\hat{\varepsilon}_i\,\hat{\varepsilon}_j}{\sum_{i=1}^{n}\hat{\varepsilon}_i^{\,2}}, \forall i, j \in N \qquad (3)$$

where w_{ij} is the generic element of a row-standardized spatial weights matrix (**W**) defined as follows:

$$w_{ij} = \frac{w_{ij}^*}{\sum_{j=1}^{n} w_{ij}^*} \qquad (4)$$

The generic element w_{ij}^* in (4) can take two different values:

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[3] Another argument that could be raised with respect to specification (2), and the consequent identification of the three effects, is that it could be misspecified as other control variables, beside country dummies, should or could be considered in explaining the spatial distribution of RDP expenditure. However, this argument is not consistent in the specification of (2) when **X** is expressed by the PRI composite indicator. In fact, as discussed in section 2.2, the PRI is computed from a large set of independent variables (for instance, per capita GDP, population density, labour market indicators, land use characteristics, remoteness), thus all of them play a role in describing the *rural effect*. Therefore, using the PRI as independent variable makes the inclusion of other control variables in (2) redundant.

$w^*_{ij} = 1$ when $i \neq j$ and $j \in N(i)$; $w^*_{ij} = 0$ when $i = j$ or $i \neq j$ and $j \notin N(i)$, where $N(i)$ is the set of neighbours of the i-th region, according to a *first-order queen contiguity matrix*. Within this approach, two regions are considered as neighbours only if they share a common boundary or vertex (Anselin, 1988). The queen contiguity matrix is preferred to other possible spatial matrix (e.g., those based on the nearest neighbours) because it better suits the case under study (NUTS3 regions across the EU27) presenting a great heterogeneity in terms of size that inevitably affect distances. However, when dealing with the contiguity matrices here adopted, a major issue is represented by islands, that clearly do not have any contiguous region. In our sample there are 25 islands. They have been considered contiguous to the closest regions in terms of geographical proximity. Eventually, each observation on average shows 5.04 neighbouring regions (i.e. links)[4].

Dealing with peculiar regions such as islands, border regions, etc.,[5] may represent a critical issue in the proper definition of **W**. Therefore, to check the robustness of results an alternative distance matrix based on the 5 nearest neighbours (and that could eliminate or shrink these measurement issues) has been also used.[6] In general, estimation results are quite robust to alternative weight matrices; thus, for its simplicity a contiguity matrix has been preferred. This row-standardized spatial weights matrix (**W**) is used to compute the global Moran's I statistic on the dependent variables, **Y**, to assess the degree of spatial dependency in the intensity of RDP expenditure, and on the estimated disturbance terms of the various alternative models, starting

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[4] Most of NUTS3 regions respectively shows 5 neighbours (18.8%), 6 neighbours (18.1%), 4 neighbours (14.6%) and 7 neighbours (13.8%).

[5] In defining this contiguity matrix, for instance, another issue is the presence of border effects. In particular, no distinction is made between trans-national neighbours and national neighbours while on the contrary, the presence of contiguous areas for regions bordering non-EU countries is neglected. Evidently, national borders may still represent an "institutional" obstacle when considering the real connectivity among regions. The same is true, in fact, even for "natural" obstacles between two regions (for instance neighbouring regions sharing a mountains chain as the main border). All these aspects are disregarded here but could be considered in a more sophisticated construction of **W**.

[6] Results are available upon request.

with the estimated residuals of the OLS model (2), $\hat{\boldsymbol{\varepsilon}}$, to assess whether spatial dependence remains after estimation.

3.3. Including the Spatial Effect: Alternative Specifications

The presence of spatial autocorrelation makes the OLS estimates biased and inconsistent. Therefore, to take it into account, model (2) can be properly modified by making the spatial effects explicit. This allows directly estimating the *pure spatial effect* and getting rid of the spatial correlation. Manski (1993) illustrates three different forms of spatial interactions that may eventually generate the observed spatial effects, that is, an observation associated with a specific location correlated with observations at other locations. Using his own terms, these three effects can be defined as follows: *endogenous interaction effect*, where the dependent variable (Y) observed in a spatial unit depends on the dependent variable of other spatial units; (ii) *exogenous interaction effect*, where the dependent variable (Y) observed in a spatial unit depends on the independent (explanatory) variables (**X**) of other spatial units; *correlated effect*, where similar unobserved environmental characteristics of other spatial units (expressed by the disturbance term, ε) result in similar behaviour of a given spatial unit.

Manski (1993) proposes a general model where all these effects are simultaneously present (the *Manski model*):

$$\begin{aligned} \mathbf{Y} &= \mathbf{D}\boldsymbol{\beta} + \gamma\mathbf{X} + \rho\mathbf{W}\mathbf{Y} + \theta\mathbf{W}\mathbf{X} + \mathbf{u} \\ \mathbf{u} &= \lambda\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon} \end{aligned} \qquad (5)$$

where **Y**, **D**, $\boldsymbol{\beta}$, **X**, γ and $\boldsymbol{\varepsilon}$ have the same meaning of (2); **W** is the (n x n) row-standardised spatial weight matrix (first-order queen contiguity matrix), θ, ρ and λ are unknown parameters expressing the *pure spatial effect*.

As in (5) all possible effects generating spatial dependence are admitted, though it represents the most general representation, all the parameters of the Manski model can not be identified. In practice, endogenous and exogenous effects can not be distinguished from each other (Manski, 1993; Elhorst, 2010: 14). A viable alternative is to impose some restrictions in the unknown parameter space thus passing from the general model (5) to a set of estimable and interpretable special cases.[7] Among these simpler model specifications we can find the OLS model, (2), itself obtainable by imposing $\theta = \rho = \lambda = 0$. The three special cases of interest here, however, are those models that selectively concentrate on one of the three abovementioned interaction effects, thus select one of the possible underlying economic mechanisms and explanations of the spatial dependence.

The first step in this direction is to assume $\rho = \lambda = 0$. Such specification thus only admits the exogenous interaction effect by simply adding to the OLS specification (2) the neighbours' average values of the independent variables:

$$\mathbf{Y} = \mathbf{D}\boldsymbol{\beta} + \gamma\mathbf{X} + \theta\mathbf{W}\mathbf{X} + \boldsymbol{\varepsilon} \tag{6}$$

where θ is the unknown parameter expressing the *pure spatial effect*.

Model (6) is called the *SLX model*. Indeed, it just accounts for the spatially-lagged independent variables (i.e., the spatial lag of X variables). Besides the usual possible problems of multicollinearity and heteroskedasticity, model (6) does not pose particular econometric problems: thus, parameters can be consistently estimated with OLS estimation. Nevertheless, the estimation of the SLX model might not eliminate the spatial correlation of the estimated disturbance terms. Therefore, after the estimation of model (6), Moran test is performed on estimated disturbances. If spatial correlation is still present in the error terms, three alternative spatial models can be specified and estimated to get rid of it.

The *Spatial Error Model* (SEM) is a special case of (5) when $\theta = \rho = 0$, that is, when separable endogenous and exogenous interaction effects are excluded. This specification includes the spatial influence within the error terms as follows (Anselin, 1988; LeSage and Pace, 2009):

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[7] More details on the relationship between the general (Manski) model and the several special cases, as well as on the consequent estimation issue, can be found in LeSage and Pace (2009) and Elhorst (2010).

$$\mathbf{Y} = \mathbf{D}\boldsymbol{\beta} + \gamma\mathbf{X} + \mathbf{u}$$
$$\mathbf{u} = \lambda\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon} \tag{7}$$

where λ is the unknown parameter indicating the spatial dependence of the error term $\boldsymbol{\varepsilon}$. Therefore, in this specification λ incorporates the *pure spatial effect*. However, (7) can not be consistently estimated with OLS estimation both for the presence of non-spherical disturbances and because the model is no longer linear in the parameters due to the new unknown parameter λ. Consistent estimates of $\boldsymbol{\beta}$, γ and λ are thus obtained by Maximum Likelihood Estimation (MLE) (Anselin, 1988; Anselin and Bera, 1998).

A further model specification making the spatial effect explicit is the *Spatial AutoRegressive* (SAR) *model*. It can be obtained as a special case of (5) when $\theta = \lambda = 0$. Therefore, it assumes that different levels of the dependent variable *Y* (i.e., the intensity of the RDP support) also depend on the levels of *Y* in neighbouring regions. In other words, spatial dependence only comes from endogenous interaction effects:

$$\mathbf{Y} = \mathbf{D}\boldsymbol{\beta} + \gamma\mathbf{X} + \rho\mathbf{W}\mathbf{Y} + \boldsymbol{\varepsilon} \tag{8}$$

where ρ is the unknown parameter expressing the *pure spatial effect*. Spatial dependence implies non-spherical disturbances and linearity in parameters does not hold true for ρ. Therefore, consistent estimation of (8) has to be performed through MLE.

A final feasible specification can more directly take into account the co-existence of separable exogenous and endogenous interaction effects. The *Spatial Durbin Model* (SDM) is the feasible (i.e., estimable) specification derived from (5) of more general validity (LeSage and Pace, 2009; Elhorst, 2010), as it admits both the exogenous and the endogenous interaction effects:

$$\mathbf{Y} = \mathbf{D}\boldsymbol{\beta} + \gamma\mathbf{X} + \rho\mathbf{W}\mathbf{Y} + \theta\mathbf{W}\mathbf{X} + \boldsymbol{\varepsilon} \tag{9}$$

where both ρ and θ are the unknown parameter expressing *pure spatial effects*.

Consistent estimation of the SDM can be obtained through MLE (LeSage and Pace, 2009; Elhorst, 2010). This model specification is encountering increasing favour in recent literature (LeSage and Pace, 2009) and it can be considered a “landmark in raising the bar in the field of applied spatial econometrics” (Elhorst, 2010: 10). One reason relies on its robustness: actually, this model specification produces unbiased coefficient estimates even when the true data-generation process is a SLX, SEM or SAR model. Moreover, it can be easily noticed that, differently from the other specifications, it does not impose any *a priori* restrictions on the magnitude of potential spatial interdependence (or spillovers) (Elhorst, 2010: 10).

To complete the picture of all feasible (i.e. identifiable and estimable) specifications of (5) we should also mention a further case where spatial interaction depends on a autocorrelation term. It is a generalization of (8) where, in fact, spatial dependence comes not only from endogenous interaction effects but also from the spatial interaction (correlation) within the error term:

$$\begin{aligned} \mathbf{Y} &= \mathbf{D}\boldsymbol{\beta} + \gamma\mathbf{X} + \rho\mathbf{WY} + \boldsymbol{\varepsilon} \\ \mathbf{u} &= \lambda\mathbf{Wu} + \boldsymbol{\varepsilon} \end{aligned} \qquad \text{(8bis)}$$

This specification is alternatively called the SARAR, the SAC or the Kelejian-Prucha model and can be estimated via MLE as well (Elhorst, 2010: 14; Bivand, 2012). Nonetheless, as Elhorst (2010: 14) clearly stresses, the SARAR specification represents an alternative to the SDM when moving from the general case, (5), towards an identifiable model. Following LeSage and Pace (2009: 155-158), Elhorst suggests that the best option between these two alternatives is to exclude the spatially autocorrelated error term as the cost of ignoring spatial dependence in the dependent and/or independent variables is relatively higher (biased and inconsistent estimate) than ignoring spatial dependence in the disturbances (loss of efficiency). This suggestion is followed here and the selection of the proper specification looks at the SDM rather than the SARAR as the most general feasible case (see Figure 4). Nonetheless, for the sake of exhaustivity, the SARAR specification is also estimated and results are reported in the Annex (Table A.3).[8]

[8] Table A.3 reports the estimates of the SARAR model only for the RDP expenditure per

3.4. Interpreting the Spatial Effect

Although all model specifications (6)-(9) make the role of space in affecting RDP expenditure intensity explicit, still the identification and economic and policy interpretation of the consequent *pure spatial effect* is not so obvious. As mentioned, the role of space is expressed through those parameters applying to the spatially lagged variables, that is, ρ, θ and λ. The nature, thus the interpretation, of the *pure spatial effect* depends on the value of these parameters.

Specifications (6) and (7) represent relatively straightforward cases. In (6) the *pure spatial effect* is given by the spatially-lagged *rural effect* and is captured by parameter θ. Therefore, it expresses how the degree of rurality of the neighbouring space affects the RDP expenditure intensity in the given region (*exogenous interaction effect)*. If parameters θ and γ share the same sign, the intensity of support received by a given region responds in the same direction to an increase (decrease) of its own degree of rurality and of the neighbouring regions. This case can be interpreted as evidence of rural/rural cooperation (integration) and of rural/urban competition. Local clusters of NUTS3 rural regions reciprocally reinforce the chance or the capacity to concentrate more RDP support. On the contrary, different signs of θ and γ may imply that the intensity of support responds in opposite directions to an increase (decrease) of its own degree of rurality and of the neighbouring regions. This case can be thus interpreted as an evidence of rural/rural competition and rural/urban cooperation (integration). A locally integrated rural-urban space reciprocally reinforces the chance or the capacity of both its rural and urban NUTS3 components to concentrate more RDP support.

In (7), the *pure spatial effect* has a different origin but is still of immediate identification and interpretation. In such case, the *pure spatial effect* is expressed by parameter λ and it is not associated to the degree or rurality (or urbanity) of the neighbouring space. Yet, in this

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hectare of UAA as dependent variable (**Y**). The other cases are available upon request. Estimation results are quite similar to the alternative specifications (the SDM in particular).

specification the RDP expenditure intensity of a given region is still affected by the over- (or under-)support[9] received by the neighbouring regions (regardless the *country* and the *rural effects*) (*correlated effect*). According to the observed sign of the spatial effect, the model can be interpreted in terms of a specific place (territorial)-based effect, unrelated to any other observable characteristic.

If parameter λ shows a positive sign, a sort of local concentration (or agglomeration) effect of the over-(under-)support is observed in the allocation of the RDP expenditure. Whether it is an over- or an under-support evidently depends on the sign of ε. Local clusters of regions, regardless of their degree of rurality, emerge with respect to their capacity to attract RDP support. Since the units under consideration are NUTS3 regions, this clustering can be also attributed to the ex-ante allocation of funds to higher NUTS levels. For instance, if a NUTS2 region receive more support that what expected given its country and degree of rurality, all the respective NUTS3 regions will tend to be over-supported, regardless the degree of rurality. On the contrary, a negative sign of λ indicates that a cross-compensation of over- and under-support is observed among neighbouring regions. Considering the ex-ante allocation to the higher NUTS levels, this cross-compensation could be viewed as an intra-NUTS2 (or higher NUTS level) compensation. Given an on-average *ex-ante* allocation of support to a NUTS2 (or higher NUTS level) region, an over-support going to some NUTS3 region, and independent from its degree of rurality, must be necessarily compensated by an under-support for some neighbouring NUTS3 regions.

In the case of the SAR model and of the SDM, the spatial effect is expressed (also) by parameter ρ which, in turn, expresses the impact on the dependent variable of a given region of the spatially lagged dependent variable (that is, of the neighbouring space). The major implication of this *endogenous interaction effect* is that it actually generates by a combination of the other two effects (*exogenous interaction* and *correlated effects)*. To appreciate this, we can notice

[9] Over- and under- here refer to what should be expected, for the given regions, given its country and its degree of rurality.

that, after a straightforward transformation, (8) can be expressed as follows:

$$\mathbf{Y} = (\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{D\beta} + \gamma(\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{X} + (\mathbf{I} - \rho\mathbf{W})^{-1}\boldsymbol{\varepsilon} \qquad (10)$$

(10) shows that in (8), and in (9) *a fortiori*, the spatial effect ρ actually expresses both the degree of rurality of the neighbouring regions (the *exogenous interaction effect*) as well as their unexplained over-(under-)support (the *correlated effect*).[10] As a consequence, also the interpretation of this spatial effect is not immediate. Whenever $\rho \neq 0$, parameters γ and θ can not be simply interpreted as the response of **Y** to a change of its own **X** and of **X** in the neighbouring space, respectively. Through endogenous interaction, this change is transmitted across space according to $\mathbf{w}$, and ρ expresses the magnitude and the direction of this transmission. The response of **Y**, therefore, is a complex combination of ρ, γ, θ (in specification (9)) and $\mathbf{w}$.

Actually, any response of the dependent variable in a given observation has to be interpreted as a combination of both *direct* and *indirect effects* (also called *impact measures*): any change to an explanatory variable in a given region jointly affects the dependent variable both in that region (*direct effect*) and in all other regions (*indirect effect*) via the presence of the spatially-lagged dependent variable (LeSage, 2008; Elhorst, 2010)[11]. Parameter γ is thus a combination of these two effects where, only the direct effect really measures what can be intended, *strictu sensu*, as the *rural effect*. The indirect effect is, in fact, a *spatial effect* though not necessarily limited to the neighbouring space. In the case of specification (9), this distinction between a direct and an indirect effect also applies to parameter θ. Here, the direct effect expresses the impact the spatially lagged **X**, therefore can be interpreted as a *local effect* as its influence is limited to neighbouring regions. On the contrary, the indirect effect

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[10] (10) also clearly shows that this spatial dependence actually implies non-spherical disturbances and non-linear parameters.

[11] As pointed out by LeSage (2008), these spatial spillovers arise as a main result of impacts that pass through neighbouring regions and back to the regions itself.

involves the **X** of all regions, therefore can be interpreted as a *global effect* (LeSage, 2008). Only the *local effect* can be given the interpretation of a local rural/rural (rural/urban) competition/cooperation, as, through parameter ρ, they spread to the whole sample of observations.

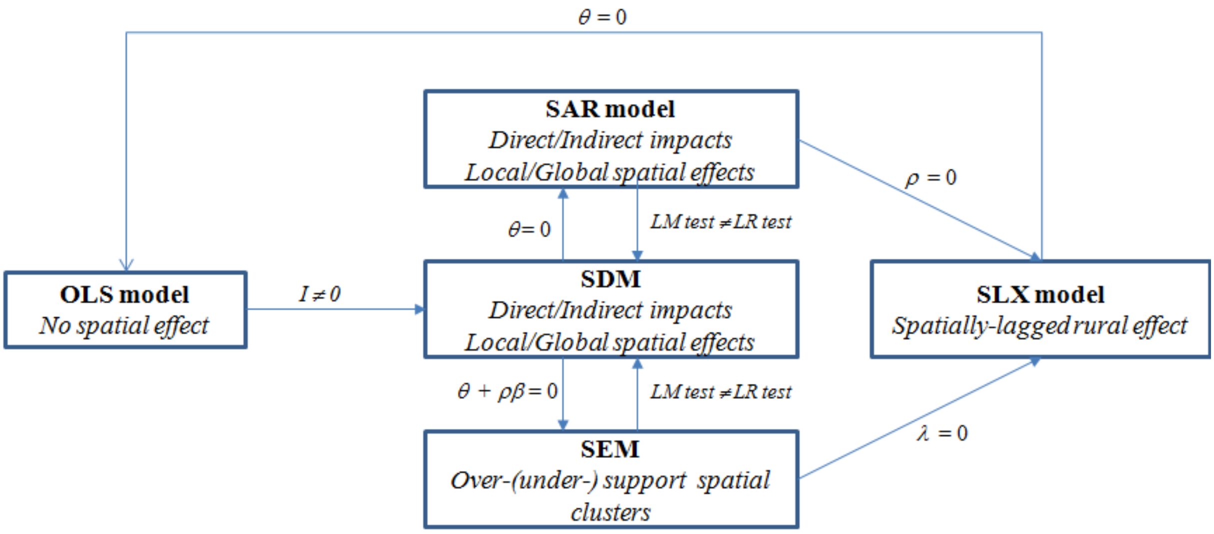
Therefore, the proper interpretation of (8) and (9) in terms of rural and spatial effects, and of these latter in terms of direct/indirect or local/global effects, can not be given but just looking at the estimated parameters as they are a combination of ρ, γ and θ (given $\mathbf{w}$). Elhorst (2010) shows how these impact measures can be obtained from the estimated parameters. Here, they are estimated by means of traces of powers of the weight matrix $\mathbf{w}$ (obtained through Monte Carlo simulations). Besides point estimates, also distributions are needed for inference purposes. Thus, Markov Chain Monte Carlo (MCMC) estimation is used to create distributions for the impact measures, providing simulated z-values and simulated p-values (LeSage, 2008; LeSage and Pace, 2009).

3.5. Testing the Proper Spatial Specification

The main consequence of this discussion on the interpretation of the spatial effect is that the choice among model specifications (2) and (6)-(9) essentially means to choose the nature of the spatial effects we are actually investigating. The specification testing procedure outlined by Elhorst (2010) is here adapted to select the best fitting specifications and it is summarized in Figure 4.

We start from the residuals of the OLS model and from the consequent abovementioned Moran test. If spatial independence is rejected ($I \neq 0$), the SDM is estimated and hypotheses H_0: $\theta = 0$ and H_0: $\theta + \rho\beta = 0$ are tested using Likelihood Ratio (LR) tests. If both hypotheses are rejected, the SDM can not be simplified to either the SAR model or the SEM and it represents the best specification. Otherwise, either the SAR model or the SEM should be chosen, provided that the Lagrange Multiplier (LM) test of spatial independence of the estimated residuals accepts the lack of correlation. On the contrary, if LM and LR tests are not concordant in indicating SAR model or SEM as correct specifications, the SDM should be adopted as it represents the more general specification (Elhorst, 2010). If the SAR model or the SEM is chosen, then LR test of $\rho = 0$ or $\lambda = 0$, respectively, is performed. If these hypotheses are not rejected, then the SLX model should be adopted and estimated and the hypothesis H_0: $\theta = 0$ tested through LM tests. If the test is accepted the OLS model is eventually adopted.

Figure 4 – Testing procedure to select the proper spatial model's specification



Source: authors' elaboration on Elhorst (2010)

4. Results

4.1. Rural Effect and Pure Spatial Effect: Some Descriptive Statistics

Descriptive statistics may preliminarily shed light on the presence of both rural and pure spatial effects. Relationships between indicators of RDP expenditure intensity and indicators of rurality are shown in Table 1. RDP expenditure intensities are significantly correlated to population density: nevertheless, this correlation is positive, thus operating in the opposite direction than expected (the more densely-populated the region, the more the expenditure intensity). Conversely, RDP expenditure intensities are not significantly correlated to the PRI, with the exception of expenditure per hectare of UAA. In this latter case, again, more central and urban regions show a greater intensity of RDP expenditure. Not univocal findings emerge when looking at the distribution of RDP expenditure among Eurostat urban-rural typologies. In this case, the Pearson correlation is replaced by the comparison of the respective averages. With regard to this categorical variable, One-Way ANOVA (Analysis of Variance) is used to test whether average values are statistically different or not. Preliminarily, the Levene's Test is computed to test whether groups' variances are equal.[12] These tests show no statistically significant differences in RDP expenditure intensities among Eurostat urban-rural typologies, with the only exception of the RDP expenditure per agricultural GVA. In this latter case, PR regions show the greatest intensity of RDP expenditure (Table 1).

Looking at these simple statistics, inconclusive evidence emerges on the direction of the rural effect. In general terms, this would indicate that the RDP is less "rural" than expected and stated in its political intentions. This result is not surprising: it was already pointed out by Shucksmith et al. (2005), although they focused on NUTS2 regions. This recurrent evidence of a negative or non-positive rural effect should be taken with caution as it depends on how we measure the degree of rurality and the expenditure intensity. In fact, observed correlations may actually hide other spatial effects. The correlation observed between RDP expenditure intensity and the degree of rurality may actually hide other effects across space (the *country effect* included) that can be confused with the rural effect. Unravelling this possible confounding effect is the main objective of the present empirical study. First of all, in order to investigate the relevance of these effects across space, global Moran's I test is performed on expenditure intensity indicators.

[12] The null hypothesis that groups variances are equal is tested. When variances among groups are equal, simple F test for the equality of means in a One-Way ANOVA is performed. Otherwise, the Welch (1951) method is adopted.

Table 1 – Relationship between the intensity of RDP support and indicators of rurality (Population density, PRI, Urban-rural typology) (p-values in parenthesis) - EU27 NUTS3 regions; 2007-2011

	RDP exp. per UAA	RDP exp. per AWU	RDP exp. per GVA
Pearson correlation coefficients:			
Population Density	0.235	0.098	0.089
	(0.000)	(0.000)	(0.002)
PRI	-0.122	-0.052	0.033
	(0.000)	(0.067)	(0.237)
Avg. comparison:			
Urban-rural typology			
Avg. PR regions	301.11	6,797.14	358.14
Avg. IR regions	288.48	8,447.46	337.62
Avg. PU regions	334.94	5,849.01	233.97
Levene's test	3.920	2.364	1.334
	(0.020)	(0.094)	(0.264)
One-way ANOVA	0.488	2.886	4.828
	(0.618)	(0.056)	(0.008)

Table 2 reports Moran tests computed, for the sake of comparison, according to two different spatial weight matrices: the first-order queen contiguity matrix adjusted for islands here adopted; a 5 nearest neighbours matrix.[13] In both cases, results suggest that spatial autocorrelation occurs across the EU space for all indicators of expenditure intensity. The question thus becomes whether the country and the rural effects are able to capture all this spatial dependence in the allocation of RDP expenditure or some further spatial effect should be considered.

Table 2 – Global Moran's I statistics for the intensity of the RDP expenditure (p-values in parenthesis) - EU27 NUTS3 regions; 2007-2011

	First-order queen contiguity matrix	5 nearest neighbours matrix
RDP exp. per UAA (€/ha)	0.2025 (0.000)	0.1654 (0.000)
RDP exp. per AWU (€/AWU)	0.1644 (0.000)	0.1789 (0.000)
RDP exp. per GVA (€/.000 €)	0.1710 (0.000)	0.1824 (0.000)

[13] For each observation, the average values of the five nearest regions is considered.

4.2. Spatial Model Estimates

Table 3 reports the estimates of models (2), (6)-(9) for the three different dependent variables (RDP expenditure intensity per UAA, per AWU, per agricultural GVA) and in three measures of rurality (PRI, Population density, Eurostat typologies). Due to space limitations, the table does not show the estimates of parameters in $\boldsymbol{\beta}$ (constant term and country effects).[14] These estimated parameters are reported in Annex (Table A.1) only for specifications referring to the RDP expenditure per UAA and rurality measured by the PRI.[15] Estimates suggest that *country effects* are mostly statistically significant, i.e., country matters in the allocation of the RDP funds. Expenditure intensity is large in many Eastern Member States and in some Western peripheral Countries (Scandinavia, Ireland and Portugal). Table 3, therefore, just shows the estimates of parameters γ (*rural effect*) and θ, λ, ρ (*pure spatial effect*) together with the tests of spatial correlation on estimated residuals (Moran and LM tests).

Another typical issues emerging in cross-sectional data (and spatial data in particular) is the presence of heteroskedasticity that could make the adopted estimators inefficient of even inconsistent (Anselin, 1988; Anselin et al., 1996). In the present case, heteroskedasticity seems likely to occur due to the wide size heterogeneity across the EU NUTS3 regions. In fact, here the effect of size heterogeneity is substantially downsized, if not eliminated, by the fact that the estimated models include variables that do not depend on the regional size as they are either ratios (the dependent variables) or indices/indicators (the rurality indicators). Nonetheless, for any model estimation the Breusch-Pagan test for heteroskedasticity is performed and respective results reported in Table 3. They indicate that

[14] It is worth noticing that that in Table 3 some parameters assume an order of magnitude that seems incompatible with the other parameters. This occurs for parameters associated to PRI and Eurostat urban-rural typologies and depends on the fact that these are indices (PRI varies between about 11 and 18) (Camaioni et al., 2013) or dummies (urban-rural typologies) while the dependent variables have an order of hundreds or thousands € per unit of UAA, AWU, GVA.

[15] Results for the other cases are available upon requests.

heteroskedasticity can be rejected in all model specifications.[16]

Limiting the discussion to statistically significant parameter estimates, we can firstly notice that in the case of OLS estimation, the PRI negatively influences the RDP expenditure per UAA, whereas it positively affects the RDP expenditure per agricultural GVA. Expressing rurality with density confirms this evidence as it positively affects the RDP expenditure per UAA. On the contrary, when rurality is expressed by the dummies associated to Eurostat urban-rural typologies, no significant parameter estimates are provided, thus confirming that such indicator of rurality may be too rough to really capture the allocation patterns across the EU space. According to these OLS estimates, however, it is confirmed that the RDP expenditure per UAA tends to be greater in more central and more urban areas, whereas it is generally lower in more rural and peripheral ones. However, the Moran tests on OLS residuals would suggest the presence of spatial autocorrelation. Not only this makes the OLS estimates biased and inconsistent. It also suggests that there are other factors, beside the country and the degree of rurality, that affects RDP fund allocation across the EU space.[17]

All spatial models (6)-(9) are legitimate candidates to get rid of the spatial correlation observed in the OLS case. Here, we comment those results that are robust across the different specifications. Generalised evidence is that, when the country effect is properly taken into account, the degree of rurality matters but it eventually operates in the opposite direction. The rural effect is found to be negative in most model specifications: the PRI negatively influences both RDP expenditure per UAA and expenditure per agricultural GVA, while

[16] Following Anselin (1988) and Fingleton (2004), the Breusch-Pagan test here performed is the Koenker-Bassett's modified version that is robust to outliers.

[17] One could argue that, if rurality is a multidimensional character, even the PRI could be a too rough measure and this can cause an artificial spatial correlation of the residuals. However, if we use the five original PCs, or some elementary variables contributing to these PCs (for instance the agricultural share within the regional economy or employment), instead of the composite PRI (Camaioni et al., 2013) to express the multiple dimensions of rurality, the model estimates do not differ much. As shown in the Annex (Table A.2), even these OLS and SLX estimates maintain spatial correlation of residuals while only few parameters associated to the 5 PCs are statistically significant.

population density positively affects them. Conversely, the rural effect plays a less important role when considering expenditure per AWU: indeed, the PRI just affects it in the SDM specification. Furthermore, in both SLX model and SDM, the spatial lag of the rural effect shows the opposite signs in almost all specifications: the extent of peripherurality (density) in neighbouring regions positively (negatively) affects RDP expenditure intensity. This seems consistent with the presence of a rural/rural competition and rural/urban integration at NUTS3 level.

In the SEM, parameter λ is positive and highly significant in all specifications, thus suggesting the existence of a "local agglomeration" effect in the allocation of the RDP rather than an "intra NUTS2 compensation" effect. In both SAR model and SDM, parameter ρ is significant, as neighbourhood matters in the allocation of RDP support. The positive sign can be interpreted as a combination of a "local agglomeration" effect and a "rural/rural competition" or "urban/rural integration" effect. Different results arise when the rural effect is expressed by means of Eurostat urban-rural typologies.[18] The associated dummies do not provide significant parameter estimates, thus confirming that those indicator may be too rough to really capture the allocation patterns across the EU space. Furthermore, within this specification, neither SLX model nor SDM can be computed, since a categorical variable can hardly be spatially lagged. Nevertheless, in both SEM and SAR model, pure spatial effect parameters (i.e., λ and ρ) are found to be positive and statistically significant in any specification.

[18] SLX and SDM models are not estimated in the case of rurality expressed by the Eurostat urban-rural typologies, as the categorical variables can not be properly spatially lagged.

Table 3 – Model estimations for the three indicators of RDP expenditure intensity and the three indicators of rurality (OLS estimates for OLS and SLX models; MLE estimates for SAR model, SEM and SDM)[a] - Standard errors (OLS, SLX) and asymptotic standard errors (SEM, SAR, SDM) in parenthesis

	RDP exp. per UAA					RDP exp. per AWU					RDP exp. per GVA				
	OLS	SLX	SEM	SAR	SDM	OLS	SLX	SEM	SAR	SDM	OLS	SLX	SEM	SAR	SDM
γ_{PRI}	-58.17*	-88.15*	-75.83*	-61.88*	-90.74*	137.5	-546.5	-312.7	-143.4	-631.7*	-7.38	-51.39*	-26.53*	-16.27	-54.99*
	(7.63)	(9.37)	(8.15)	(7.42)	(9.02)	(270.1)	(334.1)	(287.9)	(259.4)	(321.9)	(9.52)	(11.63)	(10.09)	(9.23)	(11.34)
$\theta_{PRI\ spatially\ lagged}$		75.542*			72.86*		1723.8*			1265.1*		110.94*			100.07*
		(14.01)			(13.56)		(499.6)			(481.2)		(17.40)			(16.94)
λ			0.339*					0.320*					0.277*		
			(0.035)					(0.036)					(0.037)		
ρ				0.308*	0.306*				0.312*	0.297*				0.255*	0.226*
				(0.035)	(0.036)				(0.036)	(0.036)				(0.037)	(0.038)
Moran test[b]	0.116*	0.086*				0.112*	0.095*				0.098*	0.070*			
LM test[b]				19.39*	1.92				11.12*	1.72				6.88*	3.61
Breusch-Pagan test	29.33	27.25	29.16	31.04	29.08	4.18	6.23	3.22	4.02	6.19	11.99	11.04	11.79	12.03	11.22
$\gamma_{Density}$	0.201*	0.255*	0.236*	0.208*	0.264*	1.929*	2.565*	2.585*	2.289*	2.795*	0.094*	0.157*	0.129*	0.108*	0.167*
	(0.019)	(0.021)	(0.019)	(0.018)	(0.020)	(0.677)	(0.763)	(0.685)	(0.649)	(0.731)	(0.024)	(0.027)	(0.024)	(0.023)	(0.026)
$\theta_{Density\ spatially\ lagged}$		-0.170*			-0.176*		-2.015			-1.613		-0.201*			-0.188*
		(0.031)			(0.030)		(1.121)			(1.074)		(0.039)			(0.038)
λ			0.357*					0.328*					0.288*		
			(0.035)					(0.036)					(0.037)		
ρ				0.316*	0.328*				0.322*	0.319*				0.264*	0.254*
				(0.035)	(0.035)				(0.036)	(0.036)				(0.037)	(0.037)
Moran test[b]	0.124*	0.107*				0.121*	0.116*				0.109*	0.095*			
LM test[b]				26.33*	2.75				11.73*	7.41				11.26*	0.666
Breusch-Pagan test	28.08	23.43	25.74	29.70	24.87	4.10	8.40	2.80	3.85	8.27	13.40	11.63	11.56	13.24	11.68
$\gamma_{Eurostat\ PR}$	-47.20		-36.79	-45.61		-975.2		-908.4	-1110.0		-29.45		-38.05	-39.44	
	(29.06)		(28.99)	(28.10)		(1007.1)		(998.8)	(968.3)		(35.48)		(35.40)	(34.48)	
$\gamma_{Eurostat\ PU}$	62.18		74.44	69.74		-2824.4		-2249.5	-2150.0		-98.16*		-83.03	-80.35*	
	(33.61)		(35.18)	(32.53)		(1164.8)		(1223.6)	(1120.4)		(41.04)		(42.82)	(39.90)	
λ			0.257*					0.305*					0.240*		
			(0.037)					(0.036)					(0.038)		
ρ				0.278*					0.303*					0.237*	
				(0.036)					(0.036)					(0.037)	
Moran test[b]	0.087*					0.110*					0.090*				
LM test[b]				0.73					9.47*					2.49	
Breusch-Pagan test	14.82		13.53	16.27		4.08		3.58	3.87		9.27		9.01	9.47	

* Statistically significant at the 5%

[a] Constant and country dummies' parameters are not reported (see Table A1)

[b] Both tests are performed on estimated residuals (H_0 = no spatial correlation)

4.3. *Specification Testing and Interpretation of the Rural and Spatial Effects*

Spatial models in Table 3, however, have to be intended as alternative specifications. Therefore, although results seem to be robust across all cases (OLS included), an appropriate testing procedure is needed to identify the best fitting specification. Preliminary tests on residuals (Moran tests and LM tests on residuals' autocorrelation) across all specifications show that just the SEM and the SDM get rid of the spatial autocorrelation within the error term. Conversely, both the OLS and the SLX models do not fully remove it, as indicated by the Moran test. Thus, estimation of $\boldsymbol{\beta}$, γ and θ in those models remains biased and inconsistent. The SAR model, too, can not fully remove spatial autocorrelation across residuals. Thus, the SDM emerges as the only model (together with the SEM) able to eliminate the spatial correlation of the error term in most cases.

In addition to testing for spatial correlation, a specific testing procedure is here followed to eventually corroborate the best fitting model (see section 3.5) (Anselin, 1988; Anselin et al., 1996; Elhorst, 2010). As for the OLS estimates (Table 3), table 4 shows the results of the (robust) LM tests of spatial correlation of the estimated residuals in the case of the SAR model and the SEM, and tests confirm that these specifications do not eliminate spatial dependence. Table 4 also reports the LR tests on model's parameter restrictions imposed on the SDM model. These specification tests allow assessing whether SDM can be simplified to either the SAR model or the SEM (H_0: $\theta = 0$ and H_0 : $\theta + \rho\beta = 0$, respectively). In all cases both hypotheses are rejected. Accordingly, it is possible to conclude that the SDM is the best fitting specification in most cases and take all the spatial dependence into account. The only exception is represented by the specification that includes RDP expenditure per AWU as a dependent variables and population density as a proxy of the rural effect.

All the SDM estimated parameters are statistically different from zero and are consistent and homogeneous across the alternative indicators of expenditure intensity. Looking at parameter γ estimates, both measures of rurality (PRI and density) provides perfectly concordant evidence that could be interpreted as a negative rural effect. Estimated parameter θ suggests the RDP expenditure intensity is strongly affected by spatial spillovers, that is, the support received by a region depends on the neighbouring space. In particular, the sign of this estimated parameter would confirm the presence of a rural-rural competition and rural-urban integration in the allocation of RDP funds.

As discussed in section 3.4, however, the γ and θ estimates in the SDM specification is less immediate than would be in cases without endogenous interaction. In particular, due to the presence of the spatially-lagged dependent variable in the SDM model, γ and θ do not represent the whole impact of the respective regressors, **X** and **WX** (i.e., the spatially lagged **X**). In fact, their impact on **Y** is a combination of a direct and an indirect effect. Therefore, Table 5 provides point estimates of the average direct, indirect and total effects of both **X** and **WX**, as well as their standard errors computed by means of a Markov Chain Monte Carlo (MCMC) estimation (LeSage, 2008; LeSage and Pace, 2009).[19]

Total effects associated to **X** and **WX** are generally larger than those expressed by parameters γ and θ. Direct and indirect effects are concordant in sign and are statistically significant, with the only exception of the specifications based on the RDP expenditure intensity per AWU. The main evidence emerging from Table 5, however, concerns the comparison among the three different measures of rurality and of RDP expenditure intensity. Results are homogenous across the different measures of expenditure intensity, while they are opposite comparing the two measures of rurality, PRI and Population density. In the case of PRI the rural effect is negative while, on the contrary, the spatial effect due to the rurality of the neighbouring space is positive. Of this latter effect, the largest part is a local effect while the remaining global effect is lower and not always statistically significant. This would confirm the interpretation above on the role of

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[19] As it is not identified as the best fitting specification, the SDM explaining the intensity of RDP support per AWU by means of population density as rurality indicator is not reported here.

the local rural/rural cooperation (integration) and of rural/urban competition. Results obtained with Population density as rurality indicator are, in fact, opposite. The rural effect is positive while the spatial effect generated by the neighbouring space is negative. The local effect is confirmed to be prevalent on the global effect but here the interpretation of the role of their neighborhoods is the opposite compared to PRI. The higher the degree of rurality of the neighbouring space, the lower the RDP expenditure intensity in the given region.

Despite these quite interesting results and their satisfying statistical quality, however, it is worth noticing that when expenditure intensity is expressed per AWU the SDM is not able to capture all the underlying spatial interdependence. Spatial correlation is still observed in the estimated residuals and this suggests that, despite its alleged generality, there are spatial effects that the SDM can not fully represent.

Table 4 – LM tests of spatial independence and LR specification tests on SDM estimates

	RDP exp. per UAA	RDP exp. per AWU	RDP exp. per GVA
LM tests of spatial correlation:			
PRI			
LM on SEM	36.697**	34.178**	26.353**
Robust LM on SEM	12.894**	0.005	2.623
LM on SAR model	29.359**	34.376**	24.756
Robust LM on SAR model	5.556*	0.203	1.0262
Density			
LM on SEM	41.909**	38.835**	32.633**
Robust LM on SEM	17.937**	3.103	12.468**
LM on SAR model	31.552**	37.992**	27.816**
Robust LM on SAR model	7.579**	1.259	7.650**
Eurostat PR – PU			
LM on SEM	20.392**	32.952**	22.140**
Robust LM on SEM	3.334	0.006	0.239
LM on SAR model	23.616**	33.214**	21.916**
Robust LM on SAR model	6.558*	0.267	0.015
LR tests on SDM estimates:			
$H_0 : \theta = 0$			
PRI	28.863**	6.776**	34.035**
Density	35.287**	5.572*	30.080**
$H_0 : \theta + \rho\beta = 0$			
PRI	19.210**	2.249	24.576**
Density	22.079**	0.1573	18.202**

**, *: statistically significant at the 1%, 5%, respectively

Table 5 – SDM direct, indirect and total effect estimates for **X** and **WX** according to the two different measures of rurality (simulated z-values in parenthesis)

		X		**WX**	
		PRI	*Density*	*PRI*	*Density*
RDP exp. per UAA	*Direct*	-92.76** (-9.84)	0.27** (12.9)	74.45** (5.57)	-0.18** (-5.79)
	Indirect	-37.90** (-5.16)	0.12** (5.69)	30.42** (3.89)	-0.08** (-4.04)
	Total	-130.66** (-8.76)	0.39** (10.5)	104.87** (5.22)	-0.26** (-5.36)
RDP exp. per AWU	*Direct*	-645.00* (-2.07)	-	1291.67** (2.66)	-
	Indirect	-253.98 (-1.92)	-	508.62* (2.40)	-
	Total	-898.98* (-2.05)	-	1800.29** (2.63)	-
RDP exp. per GVA	*Direct*	-55.63** (-4.79)	0.17** (6.65)	101.24** (5.94)	-0.19** (-5.08)
	Indirect	-15.44** (-3.19)	0.05** (3.99)	28.11** (3.68)	-0.06** (-3.61)
	Total	-71.07** (-4.60)	0.22** (6.19)	129.34** (5.74)	-0.25** (-4.91)

**, *: statistically significant at the 1%, 5%, respectively

5. Some Concluding Remarks

This study investigates the main drivers of the RDP expenditure allocation across the EU space by focusing on the most disaggregated territorial level (NUTS3 level) admitted by data availability. At such a territorial disaggregation, the distribution of the actual expenditure not only depends on the top-down political decisions, but also on the "local" capacity to attract and use these funds. The proposed approach explains funds' allocation as a combination of *country*, *rural* and *pure spatial effects*. The latter expresses the influence of the neighbouring space on RDP expenditure allocation and can be interpreted, in turn, in terms of rural/rural(urban) competition or integration effects, and in terms of local agglomeration or compensation effects.

The different spatial model specifications are quite concordant in suggesting some univocal and robust empirical evidence about the distribution of the RDP expenditure intensity. First of all, country matters as regions belonging to some countries tend to receive more (less) than other countries. This result is neither new nor surprising but it still suggests that disregarding the *country effect* may erroneously identify in other factors, for instance the degree of rurality, the main drivers of fund allocation. Another relevant result concerns the role of rurality. As could be expected, rurality matters in the allocation of RDP expenditure. However, many estimates are concordant in indicating that it operates in the opposite direction: the less the region is rural, the higher the expenditure intensity. A further result of the present analysis is the assessment on if and how neighbourhood matters (i.e. the spatial effect) in the allocation of RDP funds and provide some tentative interpretations for this. Estimates agree in showing that neighbouring regions play a role, though they are not always concordant in indicating the direction of this influence. Apparently, the prevailing evidence suggests that rural neighbouring regions reduce the RDP expenditure intensity thus suggesting a sort of rural/rural competition, while over- (under-) support in neighbouring regions tends to induce over- (under-) support also within the region under question ("local agglomeration" effect).

This interpretation of the rural and the pure spatial effects must be taken with caution. In fact, if we consider the SDM specification, which comes out as the most general and statistically sound spatial specification, the role of space is more complex. Direct and indirect effects can be identified and estimated for both the rural and the spatial effect, though the former (the local impact in the case of the spatial effect) largely prevails on the latter (the global impact). The rural and the spatial effects tend to compensate but their respective signs depend on how the degree of rurality is measured.

The interpretation of these results obtained with the SDM specification, in fact, represents the main challenge for future research. Three directions seem particularly interesting. From the methodological point of view, how to properly measure the degree of rurality across the EU space remains a critical empirical issue. Secondly, estimates here reported also suggest that in some cases unexplained spatial correlation may remain even adopting the SDM specification. Therefore, a further investigation of alternative spatial specifications closer to the general Manski model (5) is needed. Further refinements of this model in terms of policy analysis are desirable, as well. In particular, some recent works have already tackled the issue of disentangling RDP expenditures in single axes and measures (Camaioni et al., 2014). Indeed, both rural and spatial effects are expected to play a different role when dealing with specific RDP payments, such as agro-environment payments, or measures to improve the competitiveness of the agricultural and forestry sector.

Finally, a theoretical explanation of the spatial effect (i.e, the influence of the neighbourhoods on the RDP expenditure intensity in a given region) is still missing. Political economy models could provide useful insight into the mechanisms underlying the observed spatial distribution and dependence.

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ANNEX

Table A.1 – Constant term and country effect estimates (standard errors/asymptotic standard errors in parenthesis) - The RDP expenditure per hectare of UAA is used as dependent variable (Y) and rurality (X) is measured by the PRI

	OLS	SLX	SEM	SAR	SDM
Constant	1653.46**	953.51**	1914.59**	1514.28**	840.82**
	(134.83)	(186.08)	(151.01)	(136.09)	(184.13)
Belgium	-607.94**	-546.82**	-590.85**	-477.75**	-420.06**
	(95.97)	(95.57)	(123.33)	(93.98)	(93.71)
Bulgaria	-279.82*	-418.20**	-199.37	-154.06	-288.65**
	(109.72)	(111.49)	(141.43)	(106.08)	(107.73)
Cyprus	-123.90	-120.77	-0.90	-13.45	15.16
	(427.66)	(422.86)	(412.30)	(411.42)	(406.88)
Czech Republic	-287.69*	-309.23*	-288.16	-222.66	-244.03
	(132.99)	(131.56)	(159.40)	(128.20)	(126.82)
Germany	-511.08**	-502.53**	-508.35**	-400.70**	-393.50**
	(73.98)	(73.17)	(92.76)	(72.82)	(72.15)
Denmark	-692.01**	-615.34**	-665.32**	-537.14**	-464.69**
	(150.82)	(149.80)	(198.59)	(146.42)	(145.52)
Estonia	-320.83	-386.01	-287.06	-226.93	-290.66
	(201.29)	(199.40)	(270.23)	(193.93)	(192.13)
Spain	-594.96**	-607.65**	-575.34**	-448.85**	-462.46**
	(92.75)	(91.74)	(121.46)	(91.09)	(90.15)
Finland	-168.49	-206.96	-154.48	-136.69	-174.07
	(118.27)	(117.16)	(161.36)	(113.86)	(112.79)
France	-598.52**	-597.43**	-578.14**	-450.00**	-450.35**
	(83.45)	(82.51)	(107.69)	(82.51)	(81.70)
Greece	-321.48**	-403.88**	-291.12*	-228.18*	-308.50**
	(93.68)	(93.88)	(123.27)	(90.79)	(90.96)
Hungary	-238.70*	-279.64*	-157.57	-149.79	-190.10
	(118.10)	(117.02)	(149.83)	(113.71)	(112.68)
Ireland	-358.33*	-370.76*	-349.16	-272.08	-284.88
	(174.21)	(172.27)	(239.38)	(167.98)	(166.13)
Italy	-514.53**	-510.70**	-498.00**	-396.40**	-393.82**
	(81.93)	(81.01)	(104.96)	(80.32)	(79.47)
Lithuania	-325.70*	-416.19**	-287.74	-218.51	-306.75*
	(151.81)	(151.04)	(196.22)	(146.48)	(145.72)
Luxembourg	-406.59	-435.79	-429.33	-286.51	-315.58
	(426.75)	(422.00)	(408.18)	(410.91)	(406.29)
Latvia	-426.18*	-493.19*	-386.62	-309.10	-374.82
	(201.59)	(199.72)	(244.18)	(194.37)	(192.60)
Malta	1906.02**	1958.46**	1895.81**	1254.91**	1311.62*
	(305.81)	(302.53)	(439.46)	(302.43)	(299.62)
Netherlands	-690.11**	-619.64**	-685.17**	-545.44**	-478.87**
	(97.59)	(97.38)	(126.14)	(95.93)	(95.82)
Poland	-217.49*	-272.85**	-172.08	-138.00	-192.12*
	(88.15)	(87.76)	(114.40)	(85.00)	(84.62)
Portugal	-144.59	-195.93	-142.27	-107.13	-156.98
	(107.13)	(106.35)	(140.72)	(103.22)	(102.46)
Romania	-375.24**	-5087.56**	-288.29*	-221.25*	-351.23**
	(99.30)	(101.25)	(129.14)	(96.38)	(98.19)
Sweden	-328.77**	-337.19**	-307.90	-256.11*	-264.91*
	(116.17)	(114.88)	(157.32)	(112.15)	(110.94)
Slovenia	6.38	5.52	32.88	-6.09	-6.80
	(140.84)	(139.26)	(171.07)	(135.48)	(133.97)
Slovakia	-145.56	-164.85	-89.43	-113.22	-132.86
	(164.81)	(163.00)	(188.01)	(158.55)	(156.82)
United Kingdom	-684.51**	-625.80**	-703.84**	-538.22**	-483.74**
	(81.78)	(81.59)	(106.41)	(81.49)	(81.56)

**, *: statistically significant at the 1%, 5%, respectively

Table A.2 – OLS and SLX model parameter estimates where rurality (**X**) is expressed by the 5 PCs underlying the PRI (Camaioni et al., 2013) (standard errors/asymptotic standard errors in parenthesis)[a] - The RDP expenditure per hectare of UAA is used as dependent variable (**Y**)

	OLS	**SLX**
γ_{PC1}	37. 455**	59.891**
	(9.467)	(17.581)
γ_{PC2}	-9.412	14.947
	(11.499)	(18.673)
γ_{PC3}	-82.904**	-86.190**
	(9.751)	(14.424)
γ_{PC4}	12.383	2.376
	(10.332)	(16.766)
γ_{PC5}	18.947	57.102**
	(14.331)	(16.497)
θ_{PC1}		-25.664
		(20.538)
θ_{PC2}		-13.832
		(21.981)
θ_{PC3}		36.223
		(19.801)
θ_{PC4}		8.939
		(21.133)
θ_{PC5}		-109.204**
		(22.060)
Moran test on residuals	0.107**	0.110**

**, *: statistically significant at the 1%, 5%, respectively

[a] PCs denomination: PC1 - Economic and geographical centrality; PC2 – Demographic shrinking and ageing; PC3 – Manufacturing in rural areas with well performing labour market; PC4 – Land Use: forests vs. agricultural areas; PC5 – Urban dispersion

Table A.3 – MLE estimates of the SARAR specification (8bis) (asymptotic standard errors in parenthesis) [a] - The RDP expenditure per hectare of UAA is used as dependent variable (**Y**)

	SARAR
γ_{PRI}	-74.84* (8.35)
λ	0.310* (0.134)
ρ	0.040 (0.148)
$\gamma_{Density}$	0.235* (0.019)
λ	0.331* (0124)
ρ	0.036 (0.138)
$\gamma_{Eurostat\ PR}$	-44.22 (28.38)
$\gamma_{Eurostat\ PU}$	70.97* (33.90)
λ	0.045 (0.231)
ρ	0.242 (0.209)

* Statistically significant at the 5%

[a] Constant and country dummies' parameters are not reported (available upon request)