Project acronym: SURE-Farm
Project no.: 727520

Start date of project: June 2017
Duration: 4 years

Deliverable 2.8 "Drivers of EU regions expenditure on the Risk Management Toolkit of the CAP"

Work Performed by UOG Partner's No. 4

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Due date	31/01/2021
Version/Date	Final 26/01/2021
Work Package	WP 2
Task	T. 2.2
Task lead	UOG
Dissemination level	Public

This Project has received funds from the European Union's Horizon 2020 research and innovation programme under Grant Agreement No. 727520

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Abstract

Farming faces a wider variety of risks in comparison with other economic sectors, and the systemic nature of agricultural risks induce farmers to seek government intervention. In the EU, public interventions supporting agricultural risk management are contained in the Risk Management Toolkit (RMT) of the Common Agricultural Policy (CAP), which is a voluntary policy adopted by less than half of the EU Member States. We focus in particular on Measure 5 on "Restoring agricultural production potential damaged by natural disasters and catastrophic events and introduction of appropriate prevention actions" and Measure 17 on "Risk management" of the CAP's Rural Development policy. In order to understand the relatively low adoption of the RMT, this paper investigates the drivers of EU regions' expenditure towards the RMT by applying and comparing four types of regional-level spatial models, namely a spatial error model, a spatial autoregressive model, a spatial lag of X model and a spatial Durbin error model. Results suggest that there is a strong spatial dependence in the level of RMT expenditure. Higher expenditure towards RMT occurs in regions more exposed to environmental risks, with more land in mountainous and disadvantaged areas and with more arable, pasture and forest land. The expenditure on financial contributions for investments to restore agricultural production damaged by natural disasters is lower in agricultural intensive regions but higher in rich regions where pasture land is predominant. The expenditure for supporting insurance premiums and mutual funds is lower when the incidence of environmental risks increases and when land use is highly diversified but is higher in richer regions. Our results provide relevant insights for policymakers in the process of developing the future risk management tools of the new CAP post-2020.

1 Introduction

Farming faces a wider variety of risks in comparison with other businesses, ranging from environmental, market, financial, institutional and human or personal risks. Such risks are typically dealt with at the individual farm level, with farms adopting different risk management strategies such as agricultural insurances, production/marketing contracts and derivatives, and production or income diversification (Vigani and Kataghe, 2019). However, the systemic nature of risks makes governments responsible for maintaining farmers in agriculture and for ensuring adequate food supplies. Moreover, the costs associated with risk management (Vigani and Kataghe, 2019), the failures of agricultural insurance markets such as information asymmetries, adverse selection (Enjolrasa and Sentis, 2011) and moral hazard (Goodwin, 2001), induce farmers to ask for government's intervention.

The portfolio of tools that governments can adopt to mitigate the effects of risks on farm businesses is varied and include direct payments to stabilize farm income, specific payments for disaster assistance, trade policy instruments to stabilize domestic markets and reduce price volatility (e.g. tariff and non-tariff barriers, export subsidies, import quotas), support to mutual funds, subsidies to agricultural insurance schemes and tax regimes that help farmers to smooth the changes in income across good and bad years (Tangermann, 2011). In the European Union (EU), public interventions supporting farms are mainly concentrated in the Common Agricultural Policy (CAP). The direct payments introduced since the 2003 CAP reform provide farmers with overall income support, but specific measures for risk management have been introduced since the 2013 CAP reform through articles 36 to 39 of the EU Regulation 1305/2013 on "support for rural development by the European Agricultural Fund for Rural Development (EAFRD)", subsequently amended by the EU Regulation 2017/2393 (the Omnibus Regulation). Such articles have been transposed into support measures in the Focus Area "supporting farm risk prevention and management" (Focus Area 3B) of the Rural Development (RD) Priority on "Food Chain Organisation and Risk Management" (Priority 3) by the implementing regulation 807/2014.

According to the regulations, EU Member States (MS) and regions can voluntarily decide to allocate EAFRD funds for the support of agricultural risk management using two measures of the RD Programmes, namely, Measure 5 (M5) on "Restoring agricultural production potential damaged by natural disasters and catastrophic events and introduction of appropriate prevention actions" and Measure 17 (M17) on "Risk management". More specifically, M5 provides farms with financial contributions for investments to restore agricultural production damaged by natural disasters and M17 finalized at: i) insurance premiums and mutual funds to cover losses caused by climate changes, diseases, pests or environmental incidents; ii) mutual funds to provide compensation to farmers facing a severe drop in their income (known also as Income Stabilization

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Tool). These two measures constitute what is known as the Risk Management Toolkit (RMT) of the CAP. Despite farmers long waited and welcomed the support to risk management, only fourteen regions in twelve MS decided to adopt the RMT and only with about 1.5% of the total RD budget programmed over 2014-2020.

The aim of this paper is to investigate the drivers of EU regions' expenditure towards the RMT and to identify the potential reasons for the (relative) low voluntary adoption in certain regions and the success of the RMT in other regions. In doing so, we refer to a relatively small and recent literature studying the drivers of the CAP expenditure. Crescenzi et al. (2015) analysed the financial allocations of regional, RD and agricultural policies of the EU in order to assess their impact on territorial cohesion. Looking at the 1994–2013 period, they conclude that the territorial focus of the CAP conflicts with some of the EU cohesion policies. Zaporozhets et al. (2016) examined the determinants of the EU budget allocation in the period 1976 - 2012, identifying two alternative explanations of the EU budget distribution across the MS: i) a "needs view" linked to the principle of solidarity in which MS, with a relatively large agricultural sector and a relatively worse economic situation, are the major recipients of the EU budget; and ii) the budget allocation reflects the distribution of the MS's political power, thus MS with more power in the allocation process receive larger shares of the budget. Monsalve et al. (2016) studied the sustainability benefits of higher EAFRD spending, finding that MS with higher EAFRD endowments benefits from higher economic sustainability. Particularly relevant for our study, both in scope and methodology, is the study of Camaioni et al. (2016). For the period 2007-2011, they identify three main drivers of RD expenditure. First, country-specific drivers are due to systematic differences in rural support across MS. Second, the more a region is rural the more will spend on RD. Lastly, authors highlight the importance of a spatial driver in that the influence of bordering regions and of their degree of rurality drives regional expenditure on RD.

Our study contributes to the above-mentioned literature by addressing the particular case of RM public expenditure from the RD programs of the CAP. We use regional level data of actual EAFRD expenditure on the RMT as a whole and M5 and M17 separately taken from the European Commission's (EC) Clearance Audit Trail System (CATS). To the best of our knowledge, this is the first time such data have been used for studying the EU regions' public expenditure. We hypothesize that there are three main regional factors that have a role in national or local government decision-making on EAFRD fund allocation to the RMT; namely socio-economic, risk and environmental factors. All these factors are analysed by comparing results from four types of spatial models: i) spatial error model, ii) spatial autoregressive model, iii) spatial lag of X model, and iv) spatial Durbin error model.

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Overall, results suggest that there is a high spatial dependence in the level of regional expenditure for the RMT. More specifically: i) the RMT expenditure in one region is positively dependent on the neighbouring regions' RMT expenditures; ii) there are regional clusters of RMT expenditure across the EU; iii) the level of environmental risks and the land use (especially for pasture) of neighbouring regions affect RMT expenditure levels.

More specifically, we found that higher expenditure on RMT is observed in regions more exposed to environmental risks, with more land in mountainous and disadvantaged areas and with more arable, pasture and forest land. Interestingly, EU regions where the agricultural sector contributes more to the regional gross value added (GVA) spend less on the RMT. Expenditure on M17 is lower when the incidence of environmental risks increases and when land use is highly diversified but is higher in richer regions with high GVA per capita. Finally, expenditure on M5 is lower in agricultural intensive regions but higher in rich regions with a predominance of pasture land.

The reminder of the paper is structured as follows. The next section describes the source of data and the selection of variables measuring the drivers of RMT expenditure, and it also tests for spatial correlation of the expenditure data. Section 3 explains the methodology, while Section 4 presents the results. Finally, Section 5 concludes with some policy recommendations.

2 DATA

The analysis is developed using regional data at the third level of the Nomenclature of Territorial Units for Statistics (NUTS3). According to Camaioni et al. (2016), NUTS3 level data have the advantage not only to provide a more detailed statistical subdivision with respect the NUTS 2 or the country level, but it also allows for reducing the importance of top-down political power as driver of expenditure (Zaporozhets et al., 2016) and to account for the actual implementation of policies across space and the capacity of territories to attract and use funds. Spatial polygon data for NUTS3 regions at 1:1,000,000 scale was downloaded from the Eurostat GISCO geospatial data portal.

We hypothesize that three main regional factors exist and have a role in the national or local governments decisions of allocating EU funds for risk management: socio-economic, risk and environmental factors. Table 1 describes the variables selected, while Table 2 shows descriptive statistics.

The economic factors indicate the relative capacity of a region to cope against economic losses due to risk and disasters and also the dependence of a region's economic development on the agricultural sector. Among the economic variables, the data source for NUTS3 regions expenditure on CAP's direct payments (Pillar 1), RD payments (Pillar 2), M5 and M17 is the Clearance Audit Trail System (CATS). These are data collected yearly by the European Commission (EC) of all individual payments made to the beneficiaries of CAP's Pillars I and II for audit, control and statistical purposes. While Camaioni et al. (2016) have identified three main drivers for the distribution of total RD payments (country-specific, rurality, and spatial effects), here, we are interested in comparing what motivate EU regions for allocating part of the total RD payments to risk management instead of other RD targets (e.g. job creation, infrastructure, …etc.). Therefore, our dependent variables from the CATS are M5 payments, M17 payments, and a composite variable from the sum of both M5 and M17 payments (labelled *total RM payments*). From the CATS we also use total RD payments and total CAP subsidies (direct payments plus RD payments).

Additional social and economic factors for NUTS3 regions are captured by three main variables computed from the CATS and EUROSTAT data. These are: 1) GVA per capita: to reflect the level of economic development of the region; 2) the share of agriculture in the GVA of the region: to reflect the size and importance of the agriculture sector in a region's economy; and 3) total CAP subsidies as percentage of the value added of the agricultural sector: to reflect the level of financial support received by the agricultural sector in a region. The population data used to calculate per capita values is reported by Eurostat as of 1 January of each year, and the GVA used here is at basic prices. Because the land cover data are available only for 2018, we could not

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develop a panel data analysis and we transformed all the economic data in their four-year averages for the period from 2015 to 2018. In this way, we developed a cross-sectional analysis exploiting spatial variability instead of time variability.

As a proxy for environmental risks, we use two variables on soil erosion that are combined indicators of a number of potential environmental causes of soil erosion such as heavy rain patterns, floods and drought. The higher the soil erosion, the higher is the probability of risk exposure. Data on soil erosion for the EU28 was acquired from the EC's Join Research Centre (JRC). Two different spatial data products were downloaded; 1) Soil erosion by water (Revised Universal Soil Loss Equation - RUSLE2015) (Panagos et al., 2015); and 2) Soil erosion by wind (Revised Wind Erosion Equation – RWEQ) (Borrelli et al., 2017). Both datasets report soil loss per raster grid square (100 x 100m for water, 1km x 1km for wind) in tonnes per hectare (T/ha). Soil erosion by water is a major challenge for agriculture in the EU, and accounts for a large amount of soil loss which has a negative effect on production and agro-ecosystems. Soil erosion by water is mainly caused by precipitation, soil type, topography, land use and land management. The RUSLE2015 accounts for these factors by calculating annual soil erosion by water using rainfall erosivity factor, soil erodibility factor, cover-management factor, slope Length and slope steepness factor, and support practices factor (Panagos et al., 2015). Therefore, soil erosion by water is a proxy for rain and flood related risks. Soil erosion by wind is also a major challenge for EU agriculture in semi-arid regions of the Mediterranean as well as the temperate climate regions of the northern EU countries. Wind erosion is caused by several factors that are included in the RWEQ using weather factor, wind-erodible fraction of soil and soil crust factor, soil roughness factor, and combined vegetation factor (Borrelli et al., 2017). Therefore, soil erosion by wind is a proxy for drought related risks.

Environmental factors influence the agro-ecological condition under which farms operate. Different land cover types have different impacts and resilience against environmental risk factors, therefore they might require different levels of public support. Regarding land cover, the latest CORINE data ("CLC 2018") was downloaded in vector format from the European Environment Agency via the Copernicus data portal. The data comprises over two million spatial polygons showing the land cover for Europe across 44 classes, organised into five major land cover group types (Level 1 of the CLC): 1) artificial surfaces; 2) agricultural areas; 3) forests and semi-natural areas; 4) wetlands; 5) water bodies. That data has a minimum mapping unit of 25ha, and a reported thematic accuracy of > 85%. Spatial data showing the location of Less Favoured Areas (mountainous areas or other areas where the physical landscape results in difficult and more expensive agricultural production conditions) across the EU was downloaded from the European Environment Agency data portal. These areas, where agricultural production conditions are

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considered to be difficult, are categorised into four main classes: 1) mountain/hill areas; 2) less-favoured areas in danger of depopulation; 3) areas with specific handicaps; 4) lakes.

Table 1. Data description

Economic variables	
RM expenditure (M17 + M05) as % of total RD	Calculated as the sum of measures 5 and 17 of the RD divided by the total RD expenditure. Data obtained from the CATS dataset.
M17 expenditure as % of total RD	Calculated as measure 17 of the RD divided the total RD expenditure. Data obtained from the CATS dataset.
M05 expenditure as % of total RD	Calculated as measure 5 of the RD divided the total RD expenditure. Data obtained from the CATS dataset.
CAP subsidies (% of agriculture VA)	Calculated as total CAP expenditure divided the GVA of the agricultural sector. Data obtained from the CATS dataset and Eurostat [nama_10r_3gva].
Agricultural Value Added (% of GVA)	Calculated as the GVA of the agricultural sector divided the region's GVA. Data obtained from and Eurostat [nama_10r_3gva].
GVA per capita	Calculated as the GVA of a region divided by the region's population. Data obtained from and Eurostat [nama_10r_3gva] and [demo_r_pjangrp3].
Risk variables	
Soil erosion (wind)	Average soil erosion by wind in tonnes per ha. Data obtained from JRC.
Soil erosion (water)	Average soil erosion by water in tonnes per ha. Data obtained from JRC.
Environmental variables	
LFA (% of area)	Calculated as less favoured area divided by total area. LFA data is obtained from the European Environment Agency, and total area from CORINE land cover data.
Land diversity index	For the land diversity index, we only consider the five rural type of land (arable, crops, pastures, heterogenous agriculture, and forest). It is calculated as 1 - Simpson's Index of Diversity (D), where $D = \sum_i^R \left(\frac{a_i}{A}\right)^2$. R is the number of land types (here are 5 types of land as below), a_i is the area of each type of land, and A is the total land area. The value of the index takes the range between 0 and 1, where the greater the value the more diversity is the land, such that 1 is completely diverse land and 0 is completely homogenous land.
Arable land (% of total area)	Calculated as total arable land (CORINE codes: 211+212+213) divided total area.
Permanent crops (% of total area)	Calculated as total permanent crops land (CORINE codes: 221+222+223) divided total area.
Pastures (% of total area)	Calculated as total pastures land (CORINE codes: 231) divided total area.
Heterogeneous agriculture (% of total area)	Calculated as total heterogeneous agriculture land (CORINE codes: 241+242+243+244) divided total area.
Forest (% of total area)	Calculated as total land for forests (CORINE codes: 311+312+313) divided total area.
Country dummy	A dummy variable that takes the values from 1 to 28 for EU Member States

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Table 2. Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
(log) RM expenditure (M17 + M05) as % of total RD	1,265	-0.99	1.92	-13.45	0.90
(log) M17 expenditure as % of total RD	1,265	-0.80	1.78	-10.56	0.90
(log) M05 expenditure as % of total RD	1,265	-0.72	1.99	-13.45	0.00
(*log*) CAP subsidies (% of agri VA)	1,265	0.19	0.90	-6.88	3.26
(log) Agricultural Value Added (% of GVA)	1,265	-4.19	1.55	-10.11	-1.45
(log) LFA (% of area)	1,265	-0.90	1.66	-13.59	0.00
(log) Soil erosion (wind)	1,265	-2.57	2.72	-21.44	2.34
(log) Soil erosion (water)	1,265	0.28	1.13	-4.12	3.34
(log) Land diversity index	1,265	-0.64	0.40	-4.13	-0.26
(log) Arable land (% of total area)	1,265	-1.75	1.33	-8.52	0.00
(log) Permanent crops (% of total area)	1,265	-3.11	3.02	-12.06	0.00
(log) Pastures (% of total area)	1,265	-2.76	1.62	-12.47	0.00
(log) Heterogeneous agriculture (% of total area)	1,265	-3.29	2.00	-11.20	0.00
(log) Forest (% of total area)	1,265	-1.75	1.10	-9.46	0.00
(log) GVA per capita	1,265	-3.87	0.61	-5.89	-1.98

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3 METHODS

3.1 Ordinary least squares (OLS) model

The first model considered for estimating the drivers of RMT expenditure across EU NUTS3 regions is a simple ordinary least squares (OLS) model. The OLS model takes the form of:

$$\boldsymbol{Y} = \beta_0 + \beta_x \boldsymbol{X} + \boldsymbol{\varepsilon} \tag{1}$$

Where $\boldsymbol{Y} = y_i, (i = 1, \dots, N)$ is the dependent variable (RMT expenditure) in the form of $(N \times 1)$ vector, and N is the number of NUTS3 regions considered ($N = 1{,}265$). We use three different dependent variables $\boldsymbol{Y}$:

1) Risk management expenditure (measure 17 plus measure 05) as a percentage of total RD expenditures (RD payments or pillar 2);
2) Measure 17 expenditure as a percentage of RD payments; and
3) Measure 05 expenditure as a percentage of RD payments.

β_0 is the intercept (constant) term. $\boldsymbol{X}$ is an $(N \times K)$ matrix of exogenous variables representing:

1) CAP expenditure as a percentage of agricultural value-added;
2) Agricultural value added as a percentage of GVA;
3) Soil erosion by wind and water (average tonnes per ha);
4) Land cover: type of land cover as a percentage of total area (arable, permanent crops, pastures, heterogeneous agriculture, and forests);
5) Land diversity index;
6) Least Favourite Areas as a percentage of the total area;
7) GVA per capita; and
8) Country dummy variable.

All variables are log transformed, and CAP expenditures, agricultural value added and GVA per capita are four-years averages.

$\boldsymbol{\varepsilon}$ is the disturbance or error term that is an $(N \times 1)$ vector which OLS assumes to be independent and identically distributed (i.i.d) with an expected value of zero and a constant variance, that is $\varepsilon_n \sim (0, \sigma^2)$. Because Breusch–Pagan tests do not support the null hypothesis of constant variance, the standard errors of the reported OLS estimations are Huber-White-corrected standard errors to control for the presence of heteroskedasticity.

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Equation (1) ignores the presence of potential endogeneity (correlation between $\boldsymbol{X}$ and $\boldsymbol{\varepsilon}$) and also excludes the presence of spatial correlation across regions assuming that there is no spatial dependence. However, even after obtaining Huber-White-corrected standard errors, the White-Koenker test for heteroskedasticity rejects the null hypothesis of constant variance and that the residuals are homoscedastic. In addition, the results of the Moran test for spatial correlation among the residuals rejects the assumption that the error is i.i.d, and suggest the presence of spatial dependence among the risk management expenditures (Tables 3, 4, and 5).

3.2 Testing spatial autocorrelation and spatial data processing

Processing, analysis, and visualisation of the spatial data were conducted using the open-source software tools QGIS (v.3.14.14), GeoDa (v.1.14.0), and R (v.3.6.1 with RStudio v.1.2.5001). For the CORINE data, land cover polygons were 'intersected' with the NUTS3 region polygons and QGIS and each assigned an ID code of the NUTS3 region in which they were located (land use polygons that straddled NUTS3 boundaries were split into smaller polygons). The total land area (km^2) of each land cover type within each NUTS3 region was then calculated by grouping and summarising the attribute table of the intersected layer using R. A similar process was used to calculate the land area of the LFA polygons within each NUTS region. For the raster soil erosion data, mean T/ha was calculated across each region using the zonal statistics tools in QGIS. Testing for spatial autocorrelation

In order to assess whether a spatial regression modelling approach might be justified, a global Moran's I test (Moran, 1950) was first run (using GeoDa) to determine whether the dependent variables were spatially autocorrelated:

$$\frac{n}{S_0}\frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

where $\bar{x}$ is the mean of the x variable, w_{ij} are the elements of a weights matrix between regions *i* and *j*, and S_0 is the sum of the elements of the weights matrix: $S_0 = \sum_i \sum_j w_{ij}$. In this case, as in Camaioni et al.'s (2016) study, a first-order queen's contiguity matrix was adopted for the weights matrix, in favour of distance weighted or K-nearest neighbour (KNN) alternatives, due to the size heterogeneity of the NUTS3 regions. A Moran's I statistic reports a value of between -1 (strongly negatively autocorrelated – i.e. spatially heterogeneous with no spatial dependency) and +1 (strongly positively spatially autocorrelated with high spatial dependency).

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The first-order queen contiguity matrix ($\boldsymbol{W}$) is a positive and symmetric ($N \times N$) matrix that signifies for each observation i its neighboring spatial units (locations). Such that, $w_{ij} \neq 0$ if i and j are first-order neighbors, and $w_{ij} = 0$ if i and j are not first-order neighbors. The normalized spatial weights matrix is standardized by rows (observations), so that for any observation, the sum of its neighbors' weights are equals 1 (Anselin and Bera, 1998; Darmofal, 2015).

The resulting Moran's plot and statistic (Figures 1, 2 and 3) indicated that all dependent variables are positively spatially autocorrelated – the null hypothesis of spatial randomness can be rejected, providing justification for further analysis using spatial regression modelling.

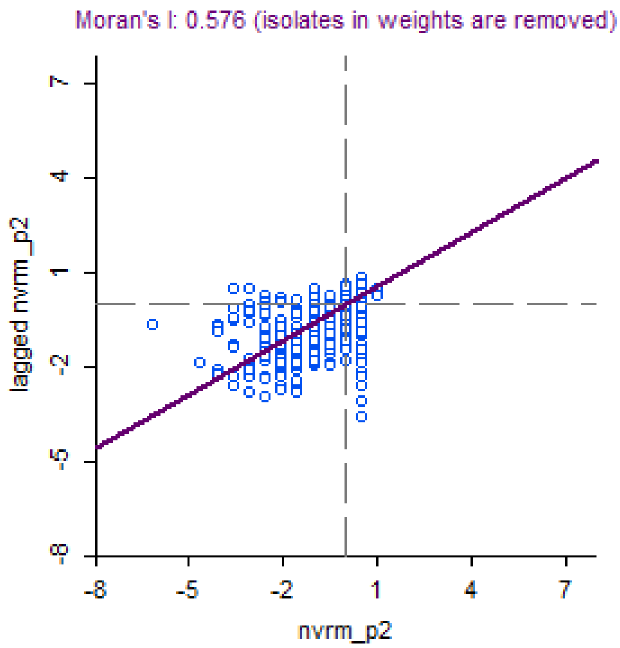

Figure 1. Moran's I plot for total RD payments in CAP's Pillar 2

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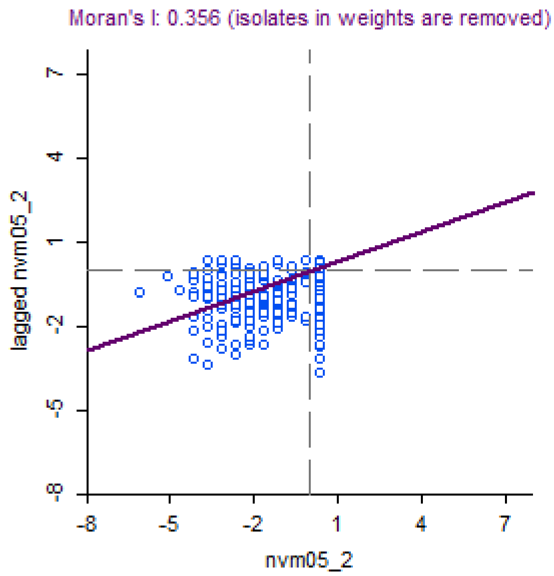

Figure 2. Moran's I plot for M5 of the RMT

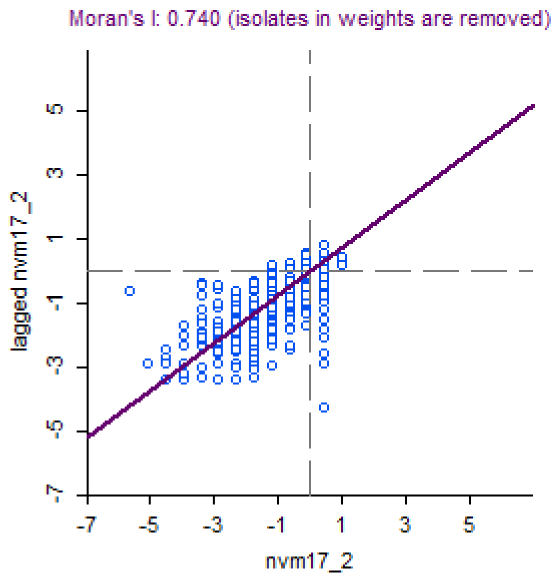

Figure 3. Moran's I plot for M17 of the RMT

The global Moran's I statistic provides useful evidence for rejecting the null hypothesis of complete spatial randomness but does not tell us which where any significant clusters or outliers are located. To visualise spatial clusters and obtain a local measure of spatial autocorrelation, we

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computed a local indicator of spatial association (LISA) statistic for the dependent variable (Anselin, 1995): $I_i = c.z_i \sum_j w_{ij} z_j$

With LISA, a local Moran statistic is computed for each observation (NUTS3 region) i by comparing its value to the spatially lagged mean of its neighbours. Importantly, the significance of the statistic for each location is reported as pseudo *p*-value, calculated using a conditional permutation approach (using *n* number of randomised permutations to compare the results to a reference distribution). The results of LISA performed on the dependent variables with the default GeoDa settings of 999 permutations and a *p*-value of 0.05 are shown in the significance maps (Figure 4a, 5a, 6a) and cluster map (Figure 4b, 5b, 6b). It is worth noting that the spatial autocorrelation detected through LISA and Moran statistic may be partially due to how the policy is managed. In general, policy decisions on RD programs affect at the same time more than one NUTS3 region. For example, in Italy some RD measures are managed at the NUTS2 level, while M17 at the national level.

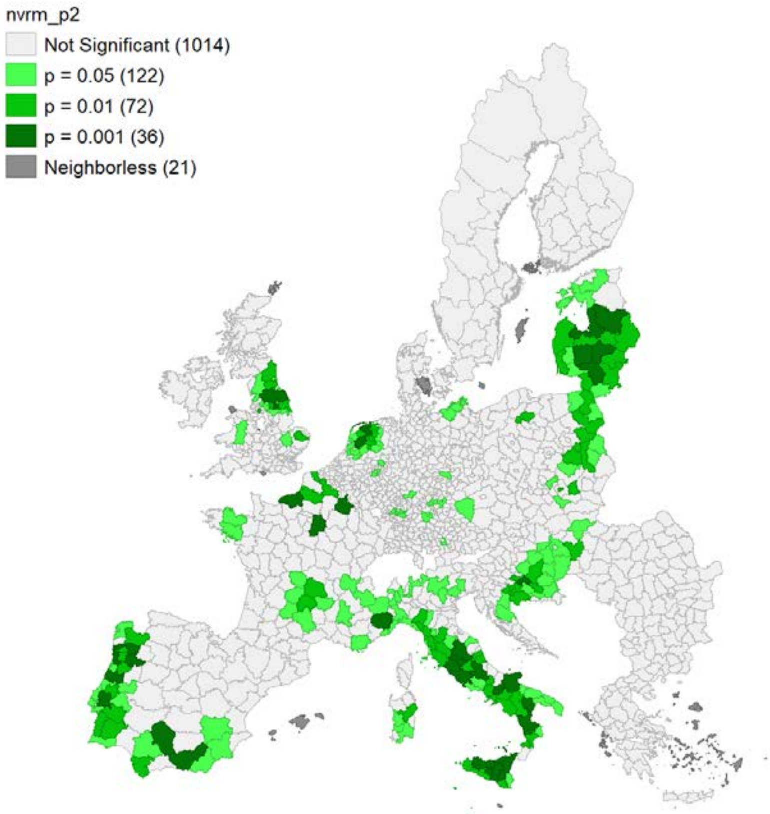

Figure 4a. Local indicators of spatial autocorrelation (LISA) significance map for RMT over Pillar 2 payments (significance of local statistic reflected in increasingly darker shades of green)

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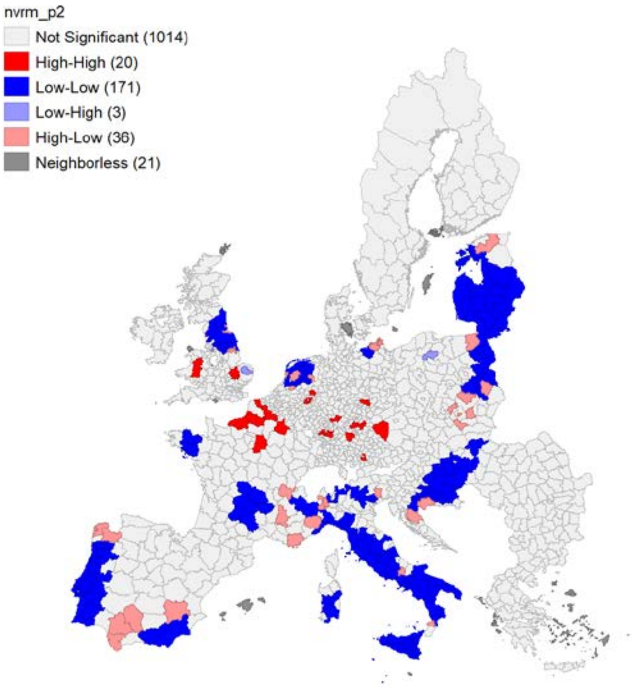

Figure 4b. Local indicators of spatial autocorrelation (LISA) cluster map for RMT over Pillar 2 payments. Map provides an indication of the type of spatial association for significant observations, based on their values in relation to neighbouring regions.

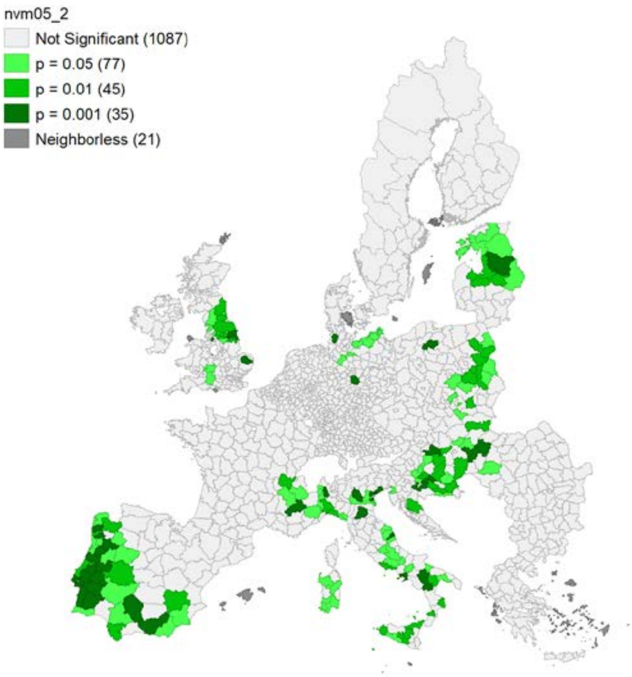

Figure 5a. Local indicators of spatial autocorrelation (LISA) significance map for Measure 5 over Pillar 2 payments (significance of local statistic reflected in increasingly darker shades of green)

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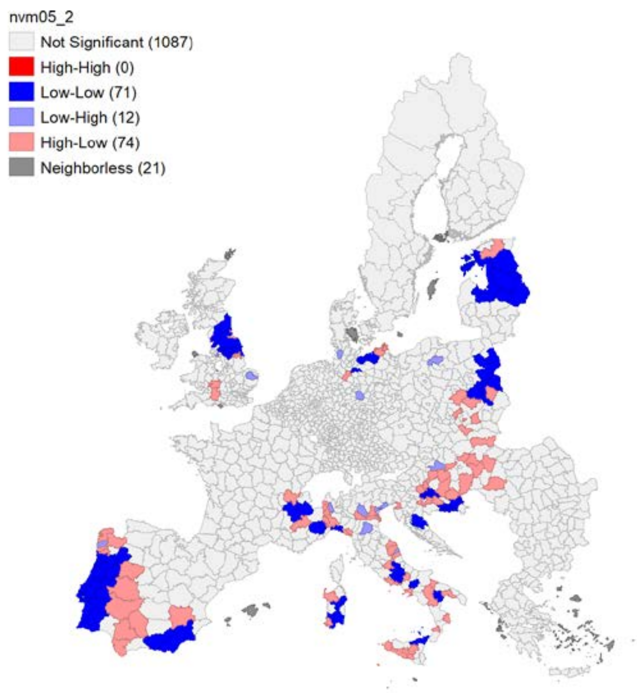

Figure 5b. Local indicators of spatial autocorrelation (LISA) cluster map for Measure 5 over Pillar 2 payments. Map provides an indication of the type of spatial association for significant observations, based on their values in relation to neighbouring regions.

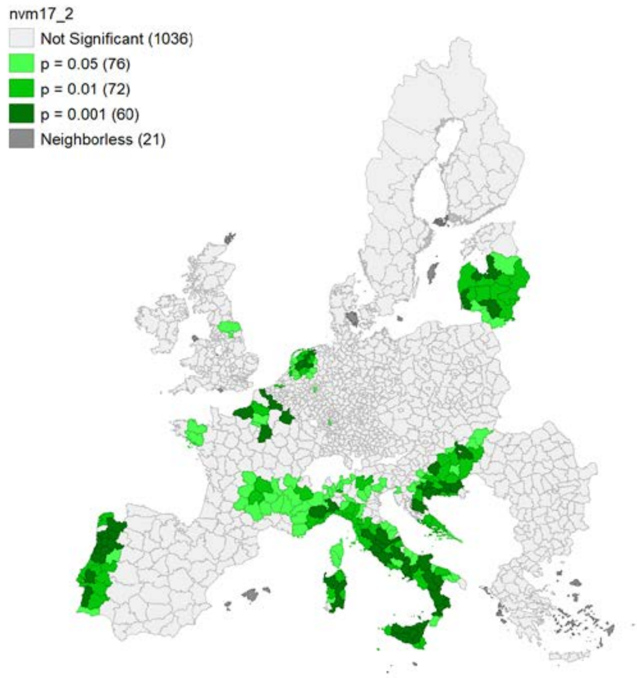

Figure 6a. Local indicators of spatial autocorrelation (LISA) significance map for Measure 17 over Pillar 2 payments (significance of local statistic reflected in increasingly darker shades of green)

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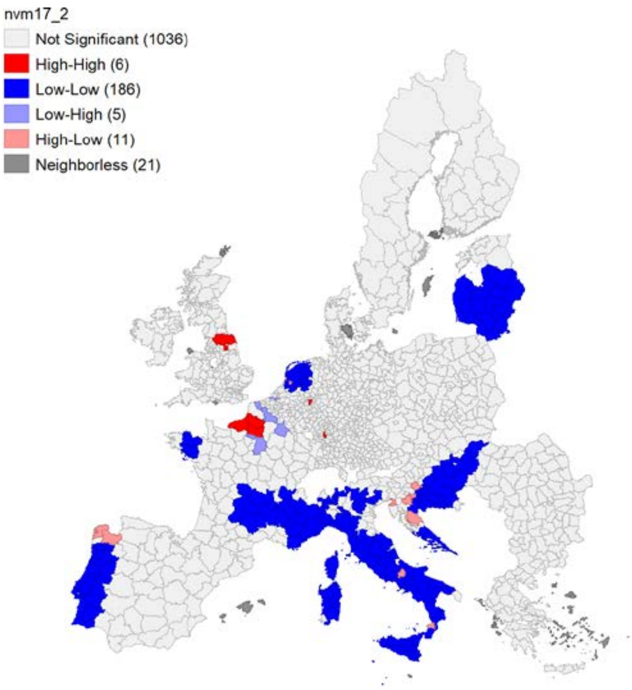

Figure 6b. Local indicators of spatial autocorrelation (LISA) cluster map for Measure 17 over Pillar 2 payments. The map provides an indication of the type of spatial association for significant observations, based on their values in relation to neighbouring regions.

3.3 Spatial autoregressive models

The spatial autocorrelation tests in the previous section confirm that M5 and M17 expenditures are spatially dependent, confirming the results of Camaioni et al. (2016) and suggesting the adoption of a spatial econometric approach accounting for spatial autocorrelation of the data at hand, instead of OLS.

Anselin and Bera (1998: 241) define spatial autocorrelation as *"the coincidence of value similarity with locational similarity. In other words, high or low values for a random variable tend to cluster in space (positive spatial autocorrelation), or locations tend to be surrounded by neighbours with very dissimilar values (negative spatial autocorrelation)".* According to Manski (1993: 532-533) and as illustrated by Camaioni et al. (2016: 443-444), there are three different types of spatial interactions which can cause spatial effects or spatial autocorrelation, which are:

1) An endogenous effect, where the observed dependent variable $\boldsymbol{y_i}$ in one spatial unit correlates with the dependent variable of other neighbouring spatial units $\boldsymbol{y_j}$;

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2) An exogenous effect, where the observed dependent variable $\boldsymbol{y_i}$ in one spatial unit correlates with the explanatory variables of other neighbouring spatial units $\boldsymbol{X_j}$; and
3) A correlated effect, where observations of the $\boldsymbol{i}$ and $\boldsymbol{j}$ spatial units are correlated due to unobserved characteristics that are represented by the disturbance term, $\boldsymbol{\varepsilon}$.

The general model proposed by Manski (1993) to account for the three spatial effects allows for spatial dependence in the dependent variable, exogenous independent variables, and spatial errors. This model can be referred to as the general nesting spatial (GNS) model and can be expressed as:

$$\boldsymbol{Y} = \beta_0 + \rho \boldsymbol{WY} + \beta_x \boldsymbol{X} + \theta \boldsymbol{WX} + \mathbf{u}$$

$$\mathbf{u} = \lambda \boldsymbol{W}\mathbf{u} + \boldsymbol{\varepsilon} \qquad (2).$$

Here, $\boldsymbol{Y}$, $\boldsymbol{X}$, β_0, β_x, and $\boldsymbol{\varepsilon}$ are similar to equation (1), and $\boldsymbol{W}$ is the $(N \times N)$ normalized spatial weight matrix. $\boldsymbol{WY}$, $\boldsymbol{WX}$, and $\boldsymbol{W}\mathbf{u}$ are $(N \times 1)$ vectors representing the spatial lags for the dependent variable $\boldsymbol{Y}$, exogenous variables $\boldsymbol{X}$, and error term $\mathbf{u}$, and ρ, θ, and λ are scalar parameters for the spatial effects that need to be estimated for the dependent variable**,** exogenous variables, and error term, respectively. Equation (2) is rarely estimated in the literature, because not all parameters are well-identified simultaneously, as endogenous and exogenous effects are not necessarily distinguished from one another (Manski, 1993; Camaioni et al., 2016: 444).

We can obtain consistent and well-identified estimations for one or two spatial dependence effects by using simpler model specifications assuming that one or two of the spatial effect parameters ρ, θ, or λ is equal to zero.

Therefore, one model that can be estimated is the spatial error model (SEM), which assumes that $\rho = \theta = 0$, and estimates the spatial effect within the error terms. The SEM can be expressed as:

$$\boldsymbol{Y} = \beta_0 + \beta_x \boldsymbol{X} + \mathbf{u}$$

$$\mathbf{u} = \lambda \boldsymbol{W}\mathbf{u} + \boldsymbol{\varepsilon} \qquad (3).$$

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The second model that can be estimated is the spatial lag of X variables (SLX) model, which assumes that $\rho = \lambda = 0$ and estimates the spatial effect of the neighbouring exogenous variables. Such that:

$$\boldsymbol{Y} = \beta_0 + \beta_x \boldsymbol{X} + \theta \boldsymbol{W}\boldsymbol{X} + \boldsymbol{\varepsilon} \qquad (4).$$

The third model is the spatial autoregressive (SAR) model, which is widely used and assumes $\theta = \lambda = 0$. The SAR model assumes also that different values of the dependent variable $\boldsymbol{Y}$ depends on the neighbouring dependent values of $\boldsymbol{Y}$. This is similar to the autoregressive models in time-series regressions, where y_t depends on its temporally lagged value y_{t-1} (Anselin and Bera, 1998: 246):

$$\boldsymbol{Y} = \beta_0 + \rho \boldsymbol{W}\boldsymbol{Y} + \beta_x \boldsymbol{X} + \boldsymbol{\varepsilon} \qquad (5).$$

A combination of the three models (SEM, SLX, and SAR) in equations (2), (3), and (4) allows for the estimation of exogenous and endogenous interaction effects simultaneously. This can be done with the spatial Durbin model (SDM) which assumes only $\lambda = 0$ and estimates the spatial effects of the exogenous variables and the dependent variable via the equation:

$$\boldsymbol{Y} = \beta_0 + \rho \boldsymbol{W}\boldsymbol{Y} + \beta_x \boldsymbol{X} + \theta \boldsymbol{W}\boldsymbol{X} + \boldsymbol{\varepsilon} \qquad (6).$$

The SDM estimates the global effects of exogenous variables or the total impacts of changes in the exogenous variables $\boldsymbol{X}$, which are complex to interpret. In the SDM, the influence of the first-order exogenous variables is not only expressed by θ, but it is also reflected in the influence of the exogenous variables of the neighbouring spatial unit, that is $\beta_j \boldsymbol{X_j}$ on $\boldsymbol{Y_j}$, which is transferred to the i spatial unit through $\rho \boldsymbol{W}\boldsymbol{Y}$. This is referred to as the global multiplier because the spillover effect of the spatially lagged dependent variable is determined by both the dependent variable itself as well as the spatial lagged exogenous variables. With the global effects, we cannot distinguish between the effect of the bordering region (first-order effects) and the effect of all other non-bordering regions in the sample, because a change in the exogenous variable of any region can potentially influence the dependent variable of all other regions (LeSage and Pace, 2009: 35).

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Similarly to the SEM, the spatial Durbin error model (SDEM) assumes only $\rho = 0$ but it estimates the spatial effects of the exogenous variables and the error term:

$$\boldsymbol{Y} = \beta_0 + \beta_x \boldsymbol{X} + \theta \boldsymbol{W}\boldsymbol{X} + \mathbf{u}$$

$$\mathbf{u} = \lambda \boldsymbol{W}\mathbf{u} + \boldsymbol{\varepsilon} \qquad (7).$$

Although the SDEM does not include a separate effect for the spatial lagged dependent variable $\boldsymbol{Y}$, it estimates the direct effects of the exogenous variables $\boldsymbol{X}$ (represented by the coefficients β) whereas the indirect effect of the neighbouring regions is represented by θ. The SDEM shows the local multipliers, or the effects of the close neighbouring spatial units (or first-order effects), instead of the global multiplier. Thus, the SDEM is more efficient for modelling first-order spatial effects, although it can underestimate higher-order (global) indirect effects (LeSage and Pace, 2009: 42). Because not all the EU MS or regions have allocated funds for the risk management tools, and given that the LISA showed clear spatial autoregressive clustering across nearby regions, the spatial effects of the drivers of risk management expenditures are essentially generated by local neighbour regions influences rather than by higher-order spatial effects produced by distant no-bordering regions.

Finally, the spatial autoregressive combined (SAC) model assumes only $\theta = 0$ and estimates the spatial effects of the dependent variable and the error term:

$$\boldsymbol{Y} = \beta_0 + \rho \boldsymbol{W}\boldsymbol{Y} + \beta_x \boldsymbol{X} + \mathbf{u}$$

$$\mathbf{u} = \lambda \boldsymbol{W}\mathbf{u} + \boldsymbol{\varepsilon} \qquad (8).$$

All the models described above can be estimated either with Generalized Spatial Two Stage Least Squares (GS2SLS) or Maximum Likelihood (ML) estimators. Whereas the ML estimator provides higher R-squared in our estimates, it is not consistent in presence of heteroscedasticity as the GS2SLS. Because we cannot reject the hypothesis of heteroskedasticity of our estimations, and because the log-likelihood function can produce inconsistent results as it assumes that the error term is i.i.d, $\boldsymbol{\varepsilon_n} \sim (\mathbf{0}, \boldsymbol{\sigma^2 I})$ (Lee, 2004), our favourite estimator is the GS2SLS. ML estimates are reported in the annexes (Annex A1, A2, and A3) for comparison purposes.

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4 RESULTS

Tables 3, 4, and 5 report the estimates of OLS (equation 1), SEM (equation 3), SLX (equation 4), SAR (equation 5), and SDEM (equation 7) for three dependent variables: i) total RM expenditure (i.e. M5 + M17) as a percentage of total RD expenditure (Table 3); ii) M17 expenditure as a percentage of total RD (Table 4); iii) M5 expenditure as a percentage of total RD (Table 5).

In our estimates, the coefficients β represent the effect of the exogenous variables $\mathbf{X}$ of the i region on its own dependent variable y_i. The spatial or regional effects are expressed through the parameters ρ, θ, and λ. In column (2), the spatial effects are expressed by the spatial error term λ, which indicates the unknown or unmeasurable spatial dependence that affects the expenditures on RM toolkit. Although λ does not indicate that the RM expenditure in a given region is correlated with a specific exogenous factor in its neighbouring regions, it still shows the presence of geographical clustering that affects the RM expenditure (Darmofal, 2015: 4).

In column (4), the spatial effect is expressed by the spatial lagged exogenous variables θ, in which the dependent variable y of the i region is also affected by the exogenous variables of its neighbouring js as well as its own exogenous variables represented by β. If the parameters of β and θ have similar signs, then the exogenous variable has similar effects on the RM expenditure of the region *i* and the neighbouring regions *j*. This can be seen as a local clustering of NUTS3 regions as neighbouring regions have similar exogenous factors that affect their RM expenditure (Camaioni et al., 2016: 447). However, if β and θ have different signs, this may mean that neighbouring regions are competing for the RM expenditure, such that the increase (decrease) of an exogenous factor in a given region has a positive (negative) effect on its RM expenditure but an opposite effect on the RM expenditure of its neighbouring regions.

The spatial effects in column (3) are relatively straightforward, as ρ indicates the spatial spillovers of the RM expenditure of the j region on its neighobouring region i. Finally, column (5) reports the spatial effects of the exogenous variables, expressed by θ, and allow for spatially dependent errors, expressed by λ.

Results are consistent across the models in the different columns, suggesting a robust empirical specification and variables choice.

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4.1 Drivers of Risk Management expenditure

We start our analysis with the spatial lag of the dependent variable ρ and the spatial lag error λ. In columns 3 of tables 3, 4, and 5 for the three estimations of total RM, M17, and M5 expenditures, there are positive and statistically significant spatial lag dependent variable ρ, suggesting the presence of spillover effects between NUTS3 regions, and that RM expenditures in one region is positively dependent on the neighbouring regions' RM expenditures. Similarly, columns (2 and 5) of the three tables show positive and statistically significant spatial lag error λ, suggesting the existence of regional clusters for the allocation of the risk management expenditures among the NUTS3 regions. The positive and statistically significant ρ and λ suggest a high spatial dependence in our estimations.

Our main parameters of interest are the drivers of risk management expenditures, which are expressed by the β and θ of the exogenous variables, and for this, we concentrate our discussion on the results of SDEM in column (5) as it provides results for both the direct and indirect impact of the exogenous variables (β and θ respectively), after controlling for spatial dependence in the spatial lagged error. In addition, the SDEM is suitable to estimate the local spatial effects instead of the global effects. This is particularly relevant as spatial effects are mainly driven by local clustering because only fourteen countries have allocated funds for the RM toolkit and as indicated by the positive and significant λ.

In column 5 of table 3, the direct effect of the exogenous variables (as indicated by β) shows that total risk management expenditure is positively and statistically significantly explained by soil erosion by wind, a higher percentage of LFA and a higher percentage of arable and forest land on total area. On the contrary, a greater agricultural value added on regional GVA has a negative and statistically significant correlation with total RM expenditure.

The coefficients θ in column 5 of table 3 indicate the negative and statistically significant indirect effect of agricultural value added on GVA. In addition, soil erosion by water and wind has indirect positive and statistically significant effects on total RM expenditure. In terms of land cover, the negative and significant θ of the land diversity index suggests that more diversified land use in neighbouring regions is associated with a lower RM expenditure of the underlying region. Finally, the percentage of the land cover of pastures and forests in neighbouring regions have a positive and statistically significant effect on the total RM expenditure of the underlying region.

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Table 3. OLS and GS2SLS estimations for drivers of Risk Management expenditure as % of total RD expenditure

	(1)	(2)	(3)	(4)	(5)
	OLS	SEM	SAR	SLX	SDEM
(β) CAP subsidies (% of agriculture VA)	0.0372	-0.0194	0.0248	-0.0573	0.0317
	(0.0633)	(0.0612)	(0.0501)	(0.0741)	(0.0634)
(β) Agricultural Value Added (% of GVA)	**-0.236*** **	**-0.0937** **	**-0.0605***	**-0.136*** **	**-0.125*** **
	(0.0394)	(0.0406)	(0.0356)	(0.0493)	(0.0462)
(β) LFA (% of area)	0.0435	0.0439	0.0408	0.0495	**0.0752** **
	(0.0364)	(0.0312)	(0.0308)	(0.0351)	(0.0329)
(β) Soil erosion (wind)	0.0200	0.00471	-0.00482	0.00174	**0.0463** **
	(0.0212)	(0.0221)	(0.0178)	(0.0247)	(0.0221)
(β) Soil erosion (water)	**-0.170*** **	**-0.221*** **	**-0.104** **	**-0.255** **	-0.134
	(0.0620)	(0.0839)	(0.0465)	(0.114)	(0.0946)
(β) Land diversity index	**-0.401*** **	-0.0646	-0.111	-0.0201	-0.139
	(0.147)	(0.133)	(0.114)	(0.163)	(0.187)
(β) Arable land (% of total area)	**0.126** **	**0.0926** **	**0.110*** **	0.0832	**0.135** **
	(0.0491)	(0.0457)	(0.0361)	(0.0574)	(0.0548)
(β) Permanent crops (% of total area)	0.00695	0.0122	0.000952	0.00305	0.00145
	(0.0171)	(0.0144)	(0.0139)	(0.0170)	(0.0175)
(β) Pastures (% of total area)	**0.0761***	0.0209	0.0317	0.00650	0.0317
	(0.0397)	(0.0334)	(0.0298)	(0.0414)	(0.0401)
(β) Heterogeneous agriculture (% of total area)	**-0.116*** **	-0.0169	-0.0334	-0.0481	0.0272
	(0.0295)	(0.0305)	(0.0270)	(0.0357)	(0.0306)
(β) Forest (% of total area)	**0.204*** **	0.0723	**0.107*** **	0.0200	**0.206*** **
	(0.0527)	(0.0524)	(0.0390)	(0.0659)	(0.0590)
(β) GVA per capita	0.00471	**0.256** **	0.102	0.0352	0.163
	(0.112)	(0.126)	(0.0834)	(0.141)	(0.130)
(β) Country dummy	**-0.0282*** **	**-0.0153***	-0.00568	-0.00172	-0.0181
	(0.00655)	(0.00900)	(0.00549)	(0.0131)	(0.0137)
Cons	**-1.294** **	0.256	0.223	**-1.158***	0.474
	(0.610)	(0.618)	(0.507)	(0.654)	(0.697)
ρ(WY)			**0.873*** **		
			(0.0923)		
(θ) CAP subsidies (% of agriculture VA)				**0.411*** **	0.195
				(0.153)	(0.152)
(θ) Agricultural Value Added (% of GVA)				**-0.186** **	**-0.336*** **
				(0.0821)	(0.100)

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(θ) LFA (% of area)				0.0618	**0.136***
				(0.0674)	(0.0774)
(θ) Soil erosion (wind)				**0.110****	**0.193*****
				(0.0483)	(0.0530)
(θ) Soil erosion (water)				0.254	**0.368*****
				(0.162)	(0.130)
(θ) Land diversity index				**-1.254*****	**-1.099***
				(0.455)	(0.596)
(θ) Arable land (% of total area)				0.0371	0.130
				(0.118)	(0.124)
(θ) Permanent crops (% of total area)				-0.0455	-0.0669
				(0.0404)	(0.0469)
(θ) Pastures (% of total area)				**0.172***	**0.283*****
				(0.0914)	(0.107)
(θ) Heterogeneous agriculture (% of total area)				**-0.131***	0.00192
				(0.0678)	(0.0774)
(θ) Forest (% of total area)				**0.451*****	**0.475*****
				(0.134)	(0.147)
(θ) GVA per capita				0.0948	-0.0410
				(0.128)	(0.122)
(θ) Country dummy				**-0.0335***	**-0.0320***
				(0.0190)	(0.0165)
λ(Wu)		**0.857*****			**0.853*****
		(0.0466)			(0.0704)
N	1265	1265	1265	1265	1265
F / Wald chi2	15.68***	54.61***	416.42***	304.54***	200.68***
R2 / Pseudo R2	0.129	0.0998	0.082	0.1658	0.1297
Wald test of spatial terms (Chi2)		338.34***	89.27***	58.49***	216.99***
White/Koenker test for heteroskedasticity (*p-value*)	0.000				
Moran test for spatial dependence (p-value)	0.000				
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively. Standard errors in parentheses.					
° Robust standard errors are in parentheses. Huber-White sandwich robust estimator was used to control for the presence of heteroscedasticity.					
OLS = ordinary least squares model; SEM = spatial error model; SAR = spatial autoregressive model (spatial lag model); SLX= spatial lag of X model; SDEM = spatial Durbin error model					

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Looking more closely to M17 expenditure, in column 5 of table 4 there is a negative and statistically significant impact of soil erosion by water. Similarly, for land cover, heterogeneous agriculture has a negative and statistically significant impact on M17 expenditure, however, arable land again has a positive and statistically significant impact on M17. In addition, there is a positive and statistically significant correlation between the level of economic development of a NUTS3 region (as measure by the GVA per capita) and its allocation of M17. Moreover, the coefficient of the θ parameter for the total CAP subsidies as a percentage of agricultural value added is positive and statistically significant. This indicates that total CAP expenditures in neighbouring regions have an indirect and positive effect on the allocation of M17 expenditure in an underlying region. Furthermore, the θ parameters show again statistically significant and negative indirect effects of land cover by heterogeneous agriculture. Similar to the results of total RM expenditure, land diversity index of neighbouring regions is statistically significant and negatively correlated with measure 17 of the underlying region, whereas the land cover of pastures of neighbouring regions has a positive and statistically significant correlation with M17. Finally, heterogeneous agriculture land of neighbouring regions has a negative and statistically significant impact on M17 expenditure of the underlying region.

Concerning M5 expenditure, column 5 of table 5 indicates that only land diversity has a statistically significant and negative effect on M5 expenditure, as expressed by β. Whereas, only agricultural value added as a percentage of GVA of neighbouring regions has a statistically significant indirect effect, which is again negatively correlated with measure 5 expenditure.

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Table 4. OLS and GS2SLS estimations for drivers of Measure 17 expenditure as % of total RD expenditure

	(1)	(2)	(3)	(4)	(5)
	OLS°	SEM	SAR	SLX	SDEM
(β) CAP subsidies (% of agriculture VA)	0.0906	-0.0610	0.0180	-0.0756	-0.0370
	(0.0617)	(0.0560)	(0.0449)	(0.0695)	(0.0567)
(β) Agricultural Value Added (% of GVA)	**-0.209*****	-0.0280	-0.0198	**-0.103****	-0.0230
	(0.0333)	(0.0322)	(0.0261)	(0.0418)	(0.0330)
(β) LFA (% of area)	0.0104	0.0299	0.0235	0.0263	0.0201
	(0.0274)	(0.0209)	(0.0190)	(0.0272)	(0.0241)
(β) Soil erosion (wind)	0.0122	-0.00288	-0.0129	-0.00706	-0.00532
	(0.0224)	(0.0242)	(0.0191)	(0.0260)	(0.0231)
(β) Soil erosion (water)	**-0.265*****	**-0.293*****	**-0.133*****	**-0.309*****	**-0.250*****
	(0.0602)	(0.0792)	(0.0437)	(0.105)	(0.0795)
(β) Land diversity index	**-0.423*****	0.0913	-0.0386	0.0353	0.0804
	(0.136)	(0.118)	(0.102)	(0.144)	(0.115)
(β) Arable land (% of total area)	**0.236*****	**0.125*****	**0.146*****	**0.125****	**0.127*****
	(0.0496)	(0.0451)	(0.0356)	(0.0571)	(0.0448)
(β) Permanent crops (% of total area)	**0.0346*****	**0.0156***	0.0103	0.0210	0.0174
	(0.0134)	(0.00860)	(0.00902)	(0.0129)	(0.0119)
(β) Pastures (% of total area)	**0.123*****	0.0294	0.0382	0.0155	0.0231
	(0.0417)	(0.0340)	(0.0303)	(0.0431)	(0.0354)
(β) Heterogeneous agriculture (% of total area)	**-0.150*****	**-0.0428*****	**-0.0437*****	**-0.0709*****	**-0.0491*****
	(0.0179)	(0.0118)	(0.0128)	(0.0167)	(0.0133)
(β) Forest (% of total area)	**0.129*****	-0.00288	**0.0651****	-0.0217	0.0136
	(0.0490)	(0.0474)	(0.0327)	(0.0605)	(0.0447)
(β) GVA per capita	-0.0706	**0.368*****	**0.124***	0.0763	**0.323*****
	(0.0988)	(0.114)	(0.0671)	(0.130)	(0.110)
(β) Country dummy	**-0.0143*****	-0.00725	-0.000830	-0.00621	-0.00422
	(0.00480)	(0.00831)	(0.00332)	(0.0105)	(0.00877)
Cons	**-1.347****	**0.978***	0.508	-0.753	0.871
	(0.542)	(0.535)	(0.401)	(0.614)	(0.530)
ρ(**WY**)			**0.932*****		
			(0.0779)		
(θ) CAP subsidies (% of agriculture VA)				**0.697*****	**0.393****
				(0.137)	(0.191)
				-0.201***	-0.0245

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(θ) Agricultural Value Added (% of GVA)				(0.0642)	(0.0752)
(θ) LFA (% of area)				0.0185	-0.0776
				(0.0551)	(0.0644)
(θ) Soil erosion (wind)				**0.110****	0.0000493
				(0.0460)	(0.0557)
(θ) Soil erosion (water)				0.204	-0.183
				(0.137)	(0.200)
(θ) Land diversity index				**-1.707*****	**-0.922****
				(0.338)	(0.373)
(θ) Arable land (% of total area)				**0.264****	0.0742
				(0.113)	(0.151)
(θ) Permanent crops (% of total area)				**0.0535***	0.0231
				(0.0282)	(0.0390)
(θ) Pastures (% of total area)				**0.257*****	**0.186***
				(0.0874)	(0.111)
(θ) Heterogeneous agriculture (% of total area)				**-0.0820***	**-0.118*****
				(0.0441)	(0.0438)
(θ) Forest (% of total area)				**0.454*****	0.0282
				(0.109)	(0.140)
(θ) GVA per capita				-0.0310	**0.221***
				(0.107)	(0.125)
(θ) Country dummy				-0.00476	-0.00869
				(0.0133)	(0.0191)
λ(Wu)		**1.017*****			**0.992*****
		(0.0482)			(0.0466)
N	1265	1265	1265	1265	1265
F / Wald chi2	19.63***	62.02***	576.24***	358.13***	80.49***
R2 / Pseudo R2	0.203	0.1408	0.1055	0.2594	0.1934
Wald test of spatial terms (Chi2)		445.89***	143.17***	124.86***	497.62***
White/Koenker test for heteroskedasticity (*p-value*)	0.000				
Moran test for spatial dependence (p-value)	0.000				

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively. Standard errors in parentheses.

° Robust standard errors are in parentheses. Huber-White sandwich robust estimator was used to control for the presence of heteroscedasticity.

OLS = ordinary least squares model; SEM = spatial error model; SAR = spatial autoregressive model (spatial lag model); SLX= spatial lag of X model; SDEM = spatial Durbin error model

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Table 5. OLS and GS2SLS estimations for drivers of Measure 5 expenditure as % of total RD expenditure

	(1)	(2)	(3)	(4)	(5)
	OLS°	SEM	SAR	SLX	SDEM
(β) CAP subsidies (% of agriculture VA)	-0.0297	-0.0466	-0.00949	-0.0458	-0.0503
	(0.0605)	(0.0629)	(0.0532)	(0.0716)	(0.0650)
(β) Agricultural Value Added (% of GVA)	**-0.100*****	-0.0546	-0.0113	-0.00931	-0.0139
	(0.0380)	(0.0398)	(0.0336)	(0.0505)	(0.0467)
(β) LFA (% of area)	0.0502	0.0561	0.0522	0.0543	0.0558
	(0.0389)	(0.0368)	(0.0362)	(0.0378)	(0.0387)
(β) Soil erosion (wind)	0.0246	0.00224	-0.00775	-0.000248	-0.00168
	(0.0253)	(0.0269)	(0.0243)	(0.0288)	(0.0271)
(β) Soil erosion (water)	-0.0809	-0.102	-0.0333	-0.123	-0.105
	(0.0656)	(0.0849)	(0.0578)	(0.119)	(0.107)
(β) Land diversity index	**-0.512*****	**-0.436*****	**-0.330*****	**-0.344****	**-0.376****
	(0.148)	(0.140)	(0.127)	(0.170)	(0.153)
(β) Arable land (% of total area)	0.0399	0.0472	**0.0692***	0.0416	0.0451
	(0.0461)	(0.0456)	(0.0397)	(0.0528)	(0.0450)
(β) Permanent crops (% of total area)	-0.00337	0.00592	-0.000844	-0.00237	-0.00419
	(0.0169)	(0.0153)	(0.0149)	(0.0165)	(0.0162)
(β) Pastures (% of total area)	**0.142*****	**0.0970****	**0.0700***	0.0734	0.0561
	(0.0451)	(0.0470)	(0.0422)	(0.0507)	(0.0477)
(β) Heterogeneous agriculture (% of total area)	-0.0407	-0.0154	-0.00272	-0.00842	0.00255
	(0.0294)	(0.0300)	(0.0262)	(0.0348)	(0.0308)
(β) Forest (% of total area)	**0.131*****	0.0480	0.0633	-0.00284	0.0430
	(0.0488)	(0.0504)	(0.0429)	(0.0601)	(0.0532)
(β) GVA per capita	**0.282****	**0.267***	0.118	**0.293***	0.187
	(0.128)	(0.147)	(0.112)	(0.155)	(0.150)
(β) Country dummy	**-0.0298*****	**-0.0222****	-0.00783	-0.00316	-0.00872
	(0.00672)	(0.00862)	(0.00616)	(0.0149)	(0.0133)
Cons	0.697	0.620	0.543	0.716	0.446
	(0.636)	(0.681)	(0.545)	(0.699)	(0.719)
ρ(WY)			**0.912*****		
			(0.150)		
(θ) CAP subsidies (% of agriculture VA)				0.0888	0.199
				(0.149)	(0.184)
				-0.224***	**-0.211****

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(θ) Agricultural Value Added (% of GVA)				(0.0848)	(0.0938)
(θ) LFA (% of area)				-0.0162	-0.0261
				(0.0680)	(0.0913)
(θ) Soil erosion (wind)				**0.122****	0.0860
				(0.0567)	(0.0719)
(θ) Soil erosion (water)				0.155	0.0840
				(0.168)	(0.191)
(θ) Land diversity index				-0.614	-0.292
				(0.516)	(0.554)
(θ) Arable land (% of total area)				-0.0364	-0.0340
				(0.119)	(0.136)
(θ) Permanent crops (% of total area)				**-0.0742***	-0.0503
				(0.0414)	(0.0485)
(θ) Pastures (% of total area)				**0.196***	0.184
				(0.113)	(0.140)
(θ) Heterogeneous agriculture (% of total area)				-0.0315	-0.114
				(0.0681)	(0.0726)
(θ) Forest (% of total area)				**0.368*****	0.167
				(0.126)	(0.142)
(θ) GVA per capita				0.0277	0.206
				(0.147)	(0.174)
(θ) Country dummy				**-0.0361***	-0.0205
				(0.0206)	(0.0213)
λ(Wu)		**0.612*****			**0.597*****
		(0.0590)			(0.0600)
N	1265	1265	1265	1265	1265
F / Wald chi2	7.48***	45.16***	150.49***	126.27***	62.86***
R2 / Pseudo R2	0.081	0.0759	0.0489	0.1028	0.0978
Wald test of spatial terms (Chi2)		107.37***	36.94***	27.66***	121.51***
White/Koenker test for heteroskedasticity (*p-value*)	0.000				
Moran test for spatial dependence (p-value)	0.000				

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively. Standard errors in parentheses.

° Robust standard errors are in parentheses. Huber-White sandwich robust estimator was used to control for the presence of heteroscedasticity.

OLS = ordinary least squares model; SEM = spatial error model; SAR = spatial autoregressive model (spatial lag model); SLX= spatial lag of X model; SDEM = spatial Durbin error model

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4.2 Direct, indirect and total effect estimates

Table 6 reports the estimates of the direct, indirect, and total average marginal effects of the drivers of RM expenditure (exogenous variables) on the reduced-form mean of the RM expenditure (dependent variable). First, the interpretation of the average direct and indirect impacts in table 6 are in line with previous results of the parameters β and θ in tables 3 to 5, suggesting once again the robustness of the analyses. Thus, here we focus on the average total impacts in Table 6.

In column 3, the average marginal total impacts of the drivers of the total RM expenditure are strongly confirmed by statistically significant higher coefficients than the ones expressed by β and θ. Specifically, we have a positive and statistically significant total marginal impact for the percentage of LFA in total area, soil erosion by wind, and land cover by arable, pastures, and forests. Whereas, land diversity and agricultural value added as a percentage of GVA have a statistically significant total marginal impact on total RM expenditure. In addition, although there is an indirect positive impact of soil erosion by water on total RM expenditure, the net total impact is statistically insignificant.

Moreover, in column 6, there are statistically significant negative total impacts of soil erosion by water, land diversity, and land cover by heterogenous agriculture on M17 expenditure. Whereas, the positive indirect impact of CAP subsidies as a percentage of agricultural value added did not lead to a statistically significant total impact. Finally, in column 9, the indirect impact of agricultural value added as a percentage of GVA have resulted in a negative and statistically significant total impact on measure 5 expenditure, while the direct impact of land diversity has no statistically significant total impact. Interestingly, while land cover by pastures and the level of economic development do not appear to have a statistically significant direct or indirect impacts on M5; their net total marginal impact is positive and statistically significant on M5 expenditure.

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Table 6. SDEM direct, indirect and total effect estimates

	RM (% of RD)			M17 (% of RD)			M05 (% of RD)		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
CAP subsidies (% of agri. VA)	0.032	0.150	0.182	-0.037	**0.304****	0.267	-0.050	0.154	0.104
	(0.063)	(0.117)	(0.135)	(0.057)	(0.147)	(0.168)	(0.065)	(0.142)	(0.142)
Agricultural VA (% of GVA)	**-0.125*****	**-0.260*****	**-0.384*****	-0.023	-0.019	-0.042	-0.014	**-0.163****	**-0.177****
	(0.046)	(0.077)	(0.092)	(0.033)	(0.058)	(0.066)	(0.047)	(0.072)	(0.071)
LFA (% of area)	**0.075****	**0.105***	**0.180****	0.020	-0.060	-0.040	0.056	-0.020	0.036
	(0.033)	(0.060)	(0.084)	(0.024)	(0.050)	(0.066)	(0.039)	(0.071)	(0.094)
Soil erosion (wind)	**0.046****	**0.149*****	**0.196*****	-0.005	0.000	-0.005	-0.002	0.066	0.065
	(0.022)	(0.041)	(0.050)	(0.023)	(0.043)	(0.050)	(0.027)	(0.056)	(0.057)
Soil erosion (water)	-0.134	**0.285*****	0.150	**-0.250*****	-0.142	**-0.391****	-0.105	0.065	-0.041
	(0.095)	(0.100)	(0.108)	(0.079)	(0.155)	(0.163)	(0.107)	(0.147)	(0.122)
Land diversity index	-0.139	**-0.849***	**-0.988***	0.080	**-0.712****	**-0.631****	**-0.376****	-0.225	-0.601
	(0.187)	(0.461)	(0.542)	(0.115)	(0.288)	(0.320)	(0.153)	(0.428)	(0.419)
Arable land (% of area)	**0.135****	0.100	**0.236****	**0.127*****	0.057	0.185	0.045	-0.026	0.019
	(0.055)	(0.096)	(0.112)	(0.045)	(0.117)	(0.130)	(0.045)	(0.105)	(0.105)
Permanent crops (% of area)	0.001	-0.052	-0.050	0.017	0.018	0.035	-0.004	-0.039	-0.043
	(0.018)	(0.036)	(0.048)	(0.012)	(0.030)	(0.040)	(0.016)	(0.037)	(0.045)
Pastures (% of area)	0.032	**0.219*****	**0.250****	0.023	**0.143***	0.167	0.056	0.142	**0.198***
	(0.040)	(0.083)	(0.099)	(0.035)	(0.085)	(0.105)	(0.048)	(0.108)	(0.112)
Heterogenous agri. (% of area)	0.027	0.001	0.029	**-0.049*****	**-0.091*****	**-0.140*****	0.003	-0.088	-0.085
	(0.031)	(0.060)	(0.077)	(0.013)	(0.034)	(0.043)	(0.031)	(0.056)	(0.061)
Forest (% of area)	**0.206*****	**0.367*****	**0.573*****	0.014	0.022	0.035	0.043	0.129	0.172
	(0.059)	(0.113)	(0.133)	(0.045)	(0.108)	(0.121)	(0.053)	(0.109)	(0.111)
GVA per capita	0.163	-0.032	0.131	**0.323*****	**0.170***	**0.493*****	0.187	0.159	**0.346****
	(0.130)	(0.094)	(0.148)	0.110)	(0.097)	(0.154)	(0.150)	(0.134)	(0.175)
Country dummy	-0.018	**-0.025***	**-0.043*****	-0.004	-0.007	-0.011	-0.009	-0.016	**-0.025****
	(0.014)	(0.013)	(0.013)	(0.009)	(0.015)	(0.014)	(0.013)	(0.016)	(0.012)
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively. Standard errors in parentheses.									

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5 CONCLUSIONS

This paper analysed the spatial, socio-economic, risk and environmental factors potentially affecting the public expenditure on the RMT funded by the EAFRD. Results suggest that there is a strong spatial dependence on the level of RMT expenditure. Higher expenditure towards RMT occurs in regions more exposed to environmental risks, with more land in mountainous and disadvantaged areas and with more arable, pasture and forest land. The expenditure on financial contributions for investments to restore agricultural production damaged by natural disasters is lower in agricultural intensive regions but higher in rich regions with a predominance of pasture land. The expenditure for supporting insurance premiums and mutual funds to cover losses caused by climate changes, diseases, pests or environmental incidents and on the IST is lower when the incidence of environmental risks increases and when land use is highly diversified but is higher in richer regions with high GVA per capita.

Currently, the EC is developing the future and new CAP that will be in place until 2027. In the new CAP proposal, the intention of supporting agricultural risk management has been confirmed and relaunched by a more integrated approached aiming at improving the resilience of the agricultural sector. This is planned through policy measures that will reinforce and enlarge those implemented in the CAP period 2014-2020 such as the RMT, aiming at stabilizing the farm income and mitigating the effects of climate change. Our results provide a number of important information for policymakers in the process of developing the future risk management tools of the new CAP.

First of all, the adoption of risk management policies follows a territorial spatial pattern. In other words, these policy tools are not adopted by EU regions in isolation, but they are driven by mutual influences of the regions nearby. This explains also the relatively low rate of adoption of the RMT. Given that the RMT was adopted by contiguous regions grouped in clusters, its adoption is linked to spill over effects probably due to sharing positive experiences with the policy and sharing similar agro-ecological conditions. Not having examples of neighbouring regions adopting such policies might have worked as a disincentive factor or, on the contrary, nearby examples might have demonstrated the utility of such policies. Examples and case studies illustrating the functionalities of risk management policies might incentivize their adoption also in regions far away from these clusters.

Second, there are a few land use types that driven the adoption of the RMT. This suggests that, on the one hand, there are a few agricultural sectors that are in more need of risk management policies than others, such as the arable, pasture and agro-forestry sectors; on the other hand, it might also suggest that the RMT was designed in such a way that was not effective or attractive for many other agricultural sectors, excluding them *de facto*. Given the highly diversified nature of EU agriculture, the design of risk management policies should consider a wider and more flexible range of sectorial needs and specificities.

Third, regions characterized by agro-ecological diversity have funded less the IST and the support to insurance and mutual funds against environmental risks. This might suggest that an agro-ecologically diversified region is less exposed to economic losses and instability thanks to the heterogeneous portfolio of economic activities and ecosystems that act as a buffer mitigating the damages of production and environmental risks.

Fourth, agricultural intensive regions spend less public money on risk management policies. This might be since in these regions the agricultural sector receives more support from direct CAP payments and other RD measures. These other forms of support also induce farm income stability and generate sufficient liquidity to deal with unexpected damages. Therefore, EAFRD funds are spent on other RD measures than the RMT. On the contrary, LFA are more likely to need RMT support against damages of an emergency nature.

However, there are still many issues that need to be explored and better understood. For example, the fact that the IST is not adopted when the incidence of environmental risks is relatively high. Therefore, additional research comparing different policy tools and their potential substitution effects are still needed.

This Project has received funds from the European Union's Horizon 2020 research and innovation programme under Grant Agreement No. 727520

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Appendix

Table A1. ML spatial estimations for drivers of Risk Management expenditure as % of total RD expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	SEM	SAR	SLX	SDM	SDEM	SAC	GNS
(β) CAP subsidies (% of agriculture VA)	-0.0202	0.0261	-0.0573	-0.0439	-0.0165	-0.0103	-0.0165
	(0.0597)	(0.0504)	(0.0755)	(0.0603)	(0.0600)	(0.0597)	(0.0599)
(β) Agricultural Value Added (% of GVA)	-0.0883**	-0.0792**	-0.136***	-0.0998**	-0.0870*	-0.0903**	-0.0859*
	(0.0440)	(0.0338)	(0.0517)	(0.0413)	(0.0458)	(0.0436)	(0.0458)
(β) LFA (% of area)	0.0438*	0.0411*	0.0495	0.0471*	0.0525*	0.0440*	0.0525*
	(0.0250)	(0.0247)	(0.0316)	(0.0253)	(0.0278)	(0.0255)	(0.0279)
(β) Soil erosion (wind)	0.00427	-0.00219	0.00174	-0.000306	0.00527	0.00346	0.00530
	(0.0179)	(0.0160)	(0.0225)	(0.0180)	(0.0184)	(0.0181)	(0.0184)
(β) Soil erosion (water)	-0.222***	-0.111***	-0.255**	-0.218***	-0.193**	-0.207***	-0.193**
	(0.0690)	(0.0418)	(0.100)	(0.0802)	(0.0775)	(0.0653)	(0.0772)
(β) Land diversity index	-0.0528	-0.142	-0.0201	0.0179	-0.0176	-0.0691	-0.0177
	(0.143)	(0.124)	(0.182)	(0.145)	(0.143)	(0.143)	(0.143)
(β) Arable land (% of total area)	0.0915**	0.112***	0.0832	0.0981**	0.0918**	0.0993**	0.0902**
	(0.0449)	(0.0351)	(0.0585)	(0.0467)	(0.0451)	(0.0443)	(0.0451)
(β) Permanent crops (% of total area)	0.0122	0.00159	0.00305	0.00688	0.000607	0.0116	0.000218
	(0.0150)	(0.0145)	(0.0190)	(0.0152)	(0.0165)	(0.0153)	(0.0166)
(β) Pastures (% of total area)	0.0184	0.0364	0.00650	-0.00176	0.00622	0.0223	0.00691
	(0.0362)	(0.0282)	(0.0474)	(0.0379)	(0.0367)	(0.0357)	(0.0367)
(β) Heterogeneous agriculture (% of total area)	-0.0131	-0.0421*	-0.0481	-0.00951	-0.0243	-0.0204	-0.0256
	(0.0270)	(0.0230)	(0.0340)	(0.0271)	(0.0275)	(0.0269)	(0.0277)
(β) Forest (% of total area)	0.0693	0.118***	0.0200	0.0516	0.0818	0.0871	0.0803
	(0.0555)	(0.0427)	(0.0724)	(0.0578)	(0.0560)	(0.0548)	(0.0559)
(β) GVA per capita	0.262*	0.0917	0.0352	0.102	0.170	0.234*	0.178
	(0.144)	(0.0922)	(0.156)	(0.124)	(0.147)	(0.138)	(0.148)
(β) Country dummy	-0.0147	-0.00808	-0.00172	-0.00925	-0.0118	-0.0149*	-0.0118
	(0.00920)	(0.00526)	(0.0131)	(0.0104)	(0.00989)	(0.00870)	(0.00986)
Cons	0.306	0.0615	-1.158	-0.384	0.00742	0.288	0.0345
	(0.711)	(0.499)	(0.723)	(0.578)	(0.734)	(0.689)	(0.735)
ρ(WY)		0.780***		0.793***		0.207*	-0.0448
		(0.0290)		(0.0293)		(0.112)	(0.127)
(θ) CAP subsidies (% of agri VA)			0.411***	0.203	0.134		0.126
			(0.155)	(0.124)	(0.193)		(0.196)
(θ) Agricultural Value Added (% of GVA)			-0.186**	0.0384	-0.0670		-0.0707
			(0.0835)	(0.0670)	(0.101)		(0.103)
(θ) LFA (% of area)			0.0618	-0.00233	0.0356		0.0364
			(0.0740)	(0.0592)	(0.0891)		(0.0902)

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(θ) Soil erosion (wind)			0.110**	0.0365	0.0365		0.0348
			(0.0464)	(0.0371)	(0.0561)		(0.0568)
(θ) Soil erosion (water)			0.254*	0.247**	0.0449		0.0272
			(0.146)	(0.117)	(0.173)		(0.178)
(θ) Land diversity index			-1.254***	-0.547*	-0.720		-0.709
			(0.409)	(0.327)	(0.493)		(0.499)
(θ) Arable land (% of total area)			0.0371	-0.111	-0.0636		-0.0648
			(0.115)	(0.0923)	(0.141)		(0.143)
(θ) Permanent crops (% of total area)			-0.0455	-0.0458	-0.0604		-0.0605
			(0.0436)	(0.0348)	(0.0528)		(0.0534)
(θ) Pastures (% of total area)			0.172*	0.0685	0.172*		0.174*
			(0.0878)	(0.0703)	(0.104)		(0.106)
(θ) Heterogeneous agriculture (% of total area)			-0.131**	-0.0856	-0.236***		-0.243***
			(0.0665)	(0.0536)	(0.0824)		(0.0842)
(θ) Forest (% of total area)			0.451***	0.0472	0.0460		0.0330
			(0.130)	(0.105)	(0.166)		(0.169)
(θ) GVA per capita			0.0948	0.00386	0.365**		0.391**
			(0.137)	(0.110)	(0.164)		(0.173)
(θ) Country dummy			-0.0335*	0.00239	-0.00904		-0.00916
			(0.0177)	(0.0142)	(0.0217)		(0.0223)
λ(**Wu**)	0.823***				0.808***	0.711***	0.828***
	(0.0276)				(0.0286)	(0.0768)	(0.0596)
/							
var(λ)	1.971***	2.012***	3.063***	1.954***	1.938***	2.028***	1.923***
	(0.187)	(0.188)	(0.215)	(0.183)	(0.182)	(0.197)	(0.185)
/							
N	1265	1265	1265	1265	1265	1265	1265
Wald chi2	56.3	1058.47	251.35	1224.96	86.86	68.43	84.59
Pseudo R2	0.0973	0.1058	0.1658	0.1471	0.1339	0.1052	0.1314
Wald test of spatial terms (Chi2)	885.85	722.6	55.88	844.67	832.08	588.7	929.54
AIC	4624.843	4632.123	5062.121	4627.118	4623.278	4624.509	4625.157
BIC	4707.128	4714.408	5206.121	4776.26	4772.42	4711.937	4779.442

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively. Standard errors in parentheses.

SEM = spatial error model; SAR = spatial autoregressive model (spatial lag model); SLX= spatial lag of X model; SDEM = spatial Durbin error model; GNS = general nesting spatial model; SAC = spatial autoregressive combined model; SDM = spatial Durbin model

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Table A2. ML spatial estimations for drivers of Measure 17 expenditure as % of total RD expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	SEM	SAR	SLX	SDM	SDEM	SAC	GNS
(β) CAP subsidies (% of agriculture VA)	-0.0611	0.0223	-0.0756	-0.0879*	-0.0366	-0.0463	-0.0489
	(0.0475)	(0.0401)	(0.0662)	(0.0475)	(0.0479)	(0.0475)	(0.0483)
(β) Agricultural Value Added (% of GVA)	-0.0278	-0.0311	-0.103**	-0.0542*	-0.0271	-0.0296	-0.0368
	(0.0355)	(0.0269)	(0.0453)	(0.0325)	(0.0366)	(0.0348)	(0.0364)
(β) LFA (% of area)	0.0299	0.0227	0.0263	0.0315	0.0208	0.0308	0.0269
	(0.0196)	(0.0197)	(0.0277)	(0.0199)	(0.0228)	(0.0201)	(0.0220)
(β) Soil erosion (wind)	-0.00289	-0.0114	-0.00706	-0.00700	-0.00529	-0.00458	-0.00453
	(0.0142)	(0.0128)	(0.0197)	(0.0141)	(0.0149)	(0.0143)	(0.0146)
(β) Soil erosion (water)	-0.293***	-0.141***	-0.309***	-0.269***	-0.248***	-0.268***	-0.240***
	(0.0575)	(0.0337)	(0.0880)	(0.0631)	(0.0609)	(0.0540)	(0.0620)
(β) Land diversity index	0.0918	-0.0614	0.0353	0.129	0.0743	0.0773	0.0816
	(0.113)	(0.0985)	(0.159)	(0.114)	(0.114)	(0.113)	(0.115)
(β) Arable land (% of total area)	0.125***	0.152***	0.125**	0.130***	0.130***	0.137***	0.138***
	(0.0361)	(0.0280)	(0.0512)	(0.0368)	(0.0360)	(0.0354)	(0.0360)
(β) Permanent crops (% of total area)	0.0156	0.0117	0.0210	0.0145	0.0179	0.0154	0.0179
	(0.0118)	(0.0116)	(0.0166)	(0.0119)	(0.0135)	(0.0121)	(0.0131)
(β) Pastures (% of total area)	0.0293	0.0432*	0.0155	0.0113	0.0241	0.0329	0.0212
	(0.0291)	(0.0225)	(0.0415)	(0.0298)	(0.0293)	(0.0286)	(0.0294)
(β) Heterogeneous agriculture (% of total area)	-0.0427**	- 0.0500***	-0.0709**	-0.0431**	-0.0509**	-0.0498**	-0.0483**
	(0.0214)	(0.0185)	(0.0298)	(0.0213)	(0.0223)	(0.0214)	(0.0220)
(β) Forest (% of total area)	-0.00293	0.0689**	-0.0217	-0.00829	0.0168	0.0196	0.0228
	(0.0446)	(0.0339)	(0.0634)	(0.0455)	(0.0445)	(0.0440)	(0.0447)
(β) GVA per capita	0.369***	0.112	0.0763	0.204**	0.310***	0.315***	0.268**
	(0.118)	(0.0735)	(0.136)	(0.0979)	(0.119)	(0.112)	(0.117)
(β) Country dummy	-0.00723	-0.00163	-0.00621	-0.00453	-0.00443	-0.00646	-0.00443
	(0.00766)	(0.00418)	(0.0114)	(0.00820)	(0.00782)	(0.00713)	(0.00791)
Cons	0.980*	0.397	-0.753	0.198	0.814	0.901	0.650
	(0.578)	(0.398)	(0.633)	(0.454)	(0.588)	(0.556)	(0.583)
ρ(**WY**)		0.876***		0.891***		0.363***	0.298*
		(0.0212)		(0.0215)		(0.100)	(0.156)
(θ) CAP subsidies (% of agri VA)			0.697***	0.326***	0.405**		0.422***
			(0.136)	(0.0978)	(0.165)		(0.151)
(θ) Agricultural Value Added (% of GVA)			-0.201***	0.0278	-0.0348		-0.0288
			(0.0731)	(0.0526)	(0.0876)		(0.0793)
(θ) LFA (% of area)			0.0185	-0.0304	-0.0761		-0.0611
			(0.0649)	(0.0466)	(0.0750)		(0.0695)
(θ) Soil erosion (wind)			0.110***	0.0252	0.00159		0.0152
			(0.0407)	(0.0292)	(0.0480)		(0.0435)
(θ) Soil erosion (water)			0.204	0.273***	-0.162		0.00704

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			(0.128)	(0.0922)	(0.154)		(0.143)
(θ) Land diversity index			-1.707***	-0.772***	-0.974**		-1.022***
			(0.358)	(0.258)	(0.417)		(0.386)
(θ) Arable land (% of total area)			0.264***	-0.0534	0.0954		0.0894
			(0.101)	(0.0731)	(0.122)		(0.112)
(θ) Permanent crops (% of total area)			0.0535	-0.00654	0.0248		0.0206
			(0.0382)	(0.0274)	(0.0445)		(0.0416)
(θ) Pastures (% of total area)			0.257***	0.0798	0.194**		0.185**
			(0.0769)	(0.0554)	(0.0897)		(0.0823)
(θ) Heterogeneous agriculture (% of total area)			-0.0820	0.0109	-0.125*		-0.0909
			(0.0583)	(0.0422)	(0.0725)		(0.0662)
(θ) Forest (% of total area)			0.454***	0.108	0.0629		0.137
			(0.114)	(0.0822)	(0.146)		(0.128)
(θ) GVA per capita			-0.0310	-0.106	0.197		0.0582
			(0.120)	(0.0861)	(0.146)		(0.132)
(θ) Country dummy			-0.00476	0.00274	-0.00952		-0.00549
			(0.0155)	(0.0111)	(0.0202)		(0.0166)
λ(Wu)	0.921***				0.907***	0.768***	0.773***
	(0.0191)				(0.0205)	(0.0679)	(0.0956)
/							
var(λ)	1.219***	1.276***	2.351***	1.210***	1.193***	1.261***	1.240***
	(0.115)	(0.121)	(0.162)	(0.111)	(0.108)	(0.121)	(0.116)
/							
N	1265	1265	1265	1265	1265	1265	1265
Wald chi2	110.74	2697.49	443.17	2950	153.64	145.57	193.11
Pseudo R2	0.1406	0.1332	0.2594	0.2131	0.2037	0.1434	0.2252
Wald test of spatial terms (Chi2)	2331.8	1702.62	96.8	2009.13	1988.08	1006.84	1000.93
AIC	4073.358	4103.117	4727.518	4070.193	4062.251	4060.198	4059.344
BIC	4155.643	4185.402	4871.517	4219.335	4211.393	4147.626	4213.629
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively. Standard errors in parentheses.							
SEM = spatial error model; SAR = spatial autoregressive model (spatial lag model); SLX= spatial lag of X model; SDEM = spatial Durbin error model; GNS = general nesting spatial model; SAC = spatial autoregressive combined model; SDM = spatial Durbin model							

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Table A3. ML spatial estimations for drivers of Measure 5 expenditure as % of total RD expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	SEM	SAR	SLX	SDM	SDEM	SAC	GNS
(β) CAP subsidies (% of agriculture VA)	-0.0482	-0.0170	-0.0458	-0.0601	-0.0497	0.00363	-0.0273
	(0.0712)	(0.0618)	(0.0815)	(0.0748)	(0.0730)	(0.0525)	(0.0704)
(β) Agricultural Value Added (% of GVA)	-0.0508	-0.0445	-0.00931	-0.00968	-0.0140	-0.0354	-0.0271
	(0.0505)	(0.0413)	(0.0558)	(0.0511)	(0.0547)	(0.0346)	(0.0537)
(β) LFA (% of area)	0.0566*	0.0515*	0.0543	0.0580*	0.0559*	0.0447	0.0548*
	(0.0312)	(0.0303)	(0.0341)	(0.0313)	(0.0320)	(0.0277)	(0.0330)
(β) Soil erosion (wind)	0.000781	0.00438	-0.000248	-0.00814	-0.00202	0.00465	-0.000716
	(0.0218)	(0.0196)	(0.0243)	(0.0223)	(0.0218)	(0.0170)	(0.0218)
(β) Soil erosion (water)	-0.103	-0.0512	-0.123	-0.121	-0.105	-0.0262	-0.0992
	(0.0730)	(0.0508)	(0.108)	(0.0994)	(0.0970)	(0.0397)	(0.0901)
(β) Land diversity index	-0.430**	-0.398***	-0.344*	-0.356**	-0.376**	-0.346***	-0.366**
	(0.171)	(0.152)	(0.196)	(0.180)	(0.175)	(0.131)	(0.167)
(β) Arable land (% of total area)	0.0475	0.0582	0.0416	0.0522	0.0452	0.0575	0.0425
	(0.0520)	(0.0430)	(0.0631)	(0.0579)	(0.0557)	(0.0360)	(0.0529)
(β) Permanent crops (% of total area)	0.00626	-0.00179	-0.00237	0.000479	-0.00408	-0.00570	-0.00278
	(0.0186)	(0.0178)	(0.0205)	(0.0188)	(0.0191)	(0.0160)	(0.0196)
(β) Pastures (% of total area)	0.0930**	0.0971***	0.0734	0.0550	0.0551	0.0852***	0.0597
	(0.0420)	(0.0347)	(0.0512)	(0.0469)	(0.0451)	(0.0293)	(0.0430)
(β) Heterogeneous agriculture (% of total area)	-0.0126	-0.0170	-0.00842	0.00537	0.00256	-0.0128	-0.0156
	(0.0322)	(0.0281)	(0.0367)	(0.0336)	(0.0330)	(0.0246)	(0.0325)
(β) Forest (% of total area)	0.0425	0.0885*	-0.00284	0.0107	0.0444	0.0843*	0.0369
	(0.0642)	(0.0522)	(0.0782)	(0.0717)	(0.0692)	(0.0433)	(0.0655)
(β) GVA per capita	0.263*	0.180	0.293*	0.192	0.184	0.135	0.209
	(0.157)	(0.113)	(0.168)	(0.154)	(0.173)	(0.0901)	(0.173)
(β) Country dummy	-0.0213**	-0.0161**	-0.00316	-0.00689	-0.00886	-0.0103**	-0.00971
	(0.00961)	(0.00645)	(0.0141)	(0.0129)	(0.0124)	(0.00503)	(0.0115)
Cons	0.604	0.601	0.716	0.409	0.436	0.509	0.427
	(0.793)	(0.612)	(0.780)	(0.716)	(0.857)	(0.502)	(0.864)
ρ(**WY**)		0.570***		0.558***		0.793***	-0.560***
		(0.0405)		(0.0415)		(0.0556)	(0.105)
(θ) CAP subsidies (% of agriculture VA)			0.0888	0.150	0.207		0.249
			(0.167)	(0.153)	(0.200)		(0.234)
(θ) Agricultural Value Added (% of GVA)			-0.224**	-0.117	-0.210**		-0.267**
			(0.0901)	(0.0832)	(0.104)		(0.123)
(θ) LFA (% of area)			-0.0162	-0.0382	-0.0265		-0.00535
			(0.0799)	(0.0733)	(0.0942)		(0.107)
(θ) Soil erosion (wind)			0.122**	0.0787*	0.0836		0.0645
			(0.0501)	(0.0460)	(0.0583)		(0.0680)
(θ) Soil erosion (water)			0.155	0.156	0.0785		-0.0513
			(0.158)	(0.145)	(0.175)		(0.214)

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(θ) Land diversity index			-0.614	-0.113	-0.268		-0.226
			(0.441)	(0.406)	(0.520)		(0.596)
(θ) Arable land (% of total area)			-0.0364	-0.0601	-0.0323		-0.00615
			(0.125)	(0.114)	(0.145)		(0.172)
(θ) Permanent crops (% of total area)			-0.0742	-0.0466	-0.0486		-0.0257
			(0.0471)	(0.0432)	(0.0558)		(0.0637)
(θ) Pastures (% of total area)			0.196**	0.0909	0.183*		0.235*
			(0.0948)	(0.0873)	(0.108)		(0.127)
(θ) Heterogeneous agriculture (% of total area)			-0.0315	-0.0406	-0.119		-0.221**
			(0.0718)	(0.0660)	(0.0841)		(0.101)
(θ) Forest (% of total area)			0.368***	0.162	0.151		0.0207
			(0.141)	(0.129)	(0.166)		(0.204)
(θ) GVA per capita			0.0277	0.0180	0.218		0.467**
			(0.148)	(0.136)	(0.166)		(0.204)
(θ) Country dummy			-0.0361*	-0.00961	-0.0195		-0.0188
			(0.0191)	(0.0176)	(0.0211)		(0.0273)
λ(**Wu**)	0.582***				0.569***	-0.428***	0.858***
	(0.0408)				(0.0413)	(0.120)	(0.0425)
/							
var(λ)	3.037***	3.024***	3.568***	3.002***	2.991***	2.773***	2.621***
	(0.275)	(0.269)	(0.288)	(0.264)	(0.264)	(0.259)	(0.243)
/							
N	1265	1265	1265	1265	1265	1265	1265
Wald chi2	41.19	328.21	144.95	361.59	65.44	547.95	73.42
Pseudo R2	0.0749	0.0837	0.1028	0.1004	0.0969	0.0755	0.0878
Wald test of spatial terms (Chi2)	203.46	197.67	30.92	216.85	211.83	489.71	805.69
AIC	5089.074	5081.205	5254.963	5094.98	5092.985	5072.294	5075.939
BIC	5171.359	5163.49	5398.962	5244.122	5242.127	5159.722	5230.224
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively. Standard errors in parentheses.							
SEM = spatial error model; SAR = spatial autoregressive model (spatial lag model); SLX= spatial lag of X model; SDEM = spatial Durbin error model; GNS = general nesting spatial model; SAC = spatial autoregressive combined model; SDM = spatial Durbin model							

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