The Role of Knowledge Spillovers and Local Government Performance in Absorption of Structural Funds

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The allocation of regional policy funds varies dramatically across regions even when one controls regional development indicators. The research question of this paper is therefore which political economy factors determine the access to financial support of regional policy funds. In order to answer this we investigate the local government performance. Governments that are already successful in the provision of public goods are presumed to be also more successful in the raising of funds. Respectively, they are better suitable to implement structural programs. Furthermore, because spatial diffusion of knowledge is one of the key factors explaining differences in economic growth, knowledge spillovers from other communities might determine local government's access to structural funds. The empirical analyses focus on the allocation of SAPARD funds in Slovakia using cross-section as well as panel data. Government performance is measured as technical efficiency of provision of local public goods derived within a non-parametric DEA approach. Spillovers are investigated using a spatial Durbin model. Additionally, it is controlled for spatial dependencies in the distribution of funds. Econometric analysis indicates that the government performance has a significant positive impact on the structural funding allocation. Furthermore spatial dependencies occur. Spillovers result from the government performance as well as from the average income. Knowledge gains from neighboring regions, and the exchange of information and experiences take place and lead to a more successful project participation.

1 Introduction

Since its beginning in 1957 the European Union is characterized by significant differences between areas in economic development and well-being. Expansion of the EU from 6 member states to currently 27 caused an increase of regional differences and resulted in the structural policy of the EU. Aim of this policy is to strengthen economic, social and territorial cohesion by reducing disparities in the level of development among regions and member states. In order to achieve this, structural programs and funds have been established to achieve the objectives of convergence, regional competitiveness and employment, and European territorial cooperation. So, regions who do not meet the convergence criteria should be supported.

Differences in the structural funds allocation among European regions are therefore not astonishing in regard to the differing levels of development. But the allocation of regional policy funds varies dramatically across regions even when one controls for regional development indicators as e.g. the average income, unemployment, the percentage of area used for agriculture or agricultural employees. Thus, the question arises which other political economy factors beyond regional development levels determine the access to financial support of regional policy funds?

In order to answer this we start by investigating if the local government performance might be a significant determinant of the structural funds-absorption. Governments that are already successful in the provision of public goods are presumed to be also more successful in the raising of funds. Respectively, they are better suitable to implement structural programs. Second, it is tested for spatial dependencies that might cause a biased distribution of structural funds, i.e. observations from nearby locations are more similar than would be expected on a random basis. In respect to the purpose of structural programs, the funds distribution might be caused by a spatial agglomeration of structural and/or landscape characteristics. Although structural characteristics are included in the explanatory variables setting, it has to be controlled for the possibility of spatial autocorrelation in the funds allocation. If the structural funds are spatially correlated, we suppose thirdly, that spillovers take place. Spillovers can occur differently. It is imaginable that a region that receives high support from structural funds will cause higher funds of the neighboring regions, too. Further, the performance and success of a local government depends probably on the knowledge and experiences the actors have. Because knowledge has a dynamic character and is transferable, knowledge-spillovers to/from neighboring regions might occur and improve the absorption-capacity. Regarding the co-financing principle of structural funds it is also thinkable that financial spillovers develop.

To deal with these considerations it is necessary to measure local government performance: Different - parametric as well as non-parametric - approaches are well discussed in literature (Balaguer-Coll et al., 2007; De Borger et al., 1994; De Borger and Kerstens, 1996). Decisive for the purpose discussed here is that the measurement is independent from the structural funds' explanatory variables, to disable endogeneity problems to occur. We decide to use a non-parametric Data Envelopment Analysis (DEA) model to receive for each investigated region a regional comparable efficiency measure and, to test for its impact on the structural funds allocation.

The second aspect we thought of is a biased selection of supported regions. Endogenous as well as exogenous processes can generate spatial structures in the structural funds' distribution. In case of endogenous processes, the spatial pattern is caused by factors that are an inherent attribute of the structural funds allocation. Otherwise, spatial autocorrelation can result from exogenous processes that are independent of the variable of interest. However, the estimation of an ordinary least squares model or in respect to panel data of a generalized least squares model would be biased caused by neglecting spatial dependencies. Therefore it is tested for spatial autocorrelation in the received SAPARD-funding. This means the structural support a region received is related to the average structural spendings the neighboring regions raised. In case of positive spatial autocorrelation the amounts of contiguous regions are similar.

Because spatial diffusion of knowledge is one of the key factors explaining differences in economic growth, knowledge spillovers from other communities might determine local government's access to structural funds. Many studies of the New Economic Geography (NEG) emphasize the importance of knowledge spillovers but do not explicitly model the process behind. We apply a spatial econometric approach to deal with the possibility of spillovers. More precisely, a spatial Durbin model is estimated to test if spillovers of knowledge, income or social capital take place. Further, a devision of the spillover effects in direct, indirect and total effects allows to compare the knowledge that is transferred from neighboring regions with the inner regional knowledge and to deduce the relative importance. The impact of neighborings' income spillovers can be compared with the one of neighboring knowledge-spillovers.

Subject of investigation are LAU 1 level regions. The spatial dimension is chosen in accordance to the first law of geography 'Everything is related, but things nearby are more related than things far away' (Tobler, 1970) and in accordance to agglomeration economies, pointing out that a large opportunity for communication of ideas and experiences is enhanced by spatial proximity (Caniels and Verspagen, 2001). Regarding the impact of local governments' performance and the possibility of knowledge spillovers the clear spatial definition of first, local governments' direct influence and second, primarily sphere of possible spillovers given by the LAU 1 level, turns out as adequate.

Additionally, the co-financing character of some structural programs supports the importance of networks as well as of localization in respect to find and contact qualified partners. Interaction patterns between local actors, like communication, might be captured technically by a network concept (Antonelli, 1996) or in a more general way by a social capital approach. We focus the importance of social capital, defined as norms and networks that allow collective action for economic growth (Knack and Keefer, 1997). The regional endowment with social capital is considered as a further component leading to a successfully program participation.

Although spatial autoregressive models as well as the importance of knowledge/ knowledge spillovers for the success of projects or enterprises have been known for years, they have not been applied to explain differences in the structural funds distribution, yet (as far as the authors know). The same applies to the impact of government performance. All the more, this paper aims to examine to what extent the received structural funds of 72 Slovakian regions are determined by the government performance as well as by spatial dependencies, in particular by knowledge spillovers among districts. Beyond, in respect to the general purpose of structural programs to support lagging behind regions and to improve their quality of life, a synthetic regional quality of life measure is deduced as an explanatory variable and included in the investigation. The aim of this study is to clarify the determinants of the structural funds' allocation and, to deduce possible room of improvement for the implementation of structural policy measures of the European Union. Subject of investigation is the special accession program for agriculture and rural development - SAPARD which was one of the pre-accession instruments for the Central and Eastern European member-states. Spatial econometric models are estimated, using cross sectional as well as panel-data.

In the following section the importance of local government performance as well as of knowledge spillovers is introduced; next the characteristics of the SAPARD-program are discussed before a description of the data base is given. The econometric estimation approach is constituted before the estimation results are presented and discussed. Finally section 6 concludes this paper.

2 Background and Motivation: Government Performance, Spatial Dependencies and Knowledge Spillovers

In case regional development indicators do not explain structural funds allocation sufficiently, other political economy factors might determine the funds distribution. Following general contributions of the political economy (Magee et al., 1989; Persson and Tabellini, 2000) we investigated the local government performance. The motivation to consider this approach is multifarious. In most European countries local governments have a power of general competence to undertake any activities which they consider to be in the interest of the local public, unless already undertaken by other bodies. The economic theory emphasizes the instrumental role of local government in providing public services and seeks to determine the conditions of maximization of economic welfare[1]. Allocation, distribution, regulation and stabilization are well known governmental roles (Bailey, 1995). Stabilization and income distribution are mostly the concern of national governments, whereas resource allocation is in the hands of of local governments (Oates, 1972; King, 1984; Musgrave and Musgrave, 1989).

However, the local government is responsible for the public goods provision. It seems obvious that a local government that provides public goods efficient, respectively performs well might be better suited in other fields of policy planning, too. We assume that high performing local governments implement structural programs more successful than less-performing ones. Further, the strengthened decentralization of program implementation as in case of the SAPARD program implies a generally increased importance of local agencies and local governments.

It should be clear that local governments differ in performing these tasks. The performance measurement can be used as benchmark competition for improving performance but also as managerial decision making tool or as a stimulation of policy development (Dollery and Wallis, 2001). The measurement of performance is problematic as local governments are concerned with accountability, transparency, efficiency and effectiveness. Moreover, difficulties in measurement occur in multiple and/or complex outputs which are produced (Mark, 1986; Hatry and Fisk, 1992), especially as the final outcome as well as side-effects become apparent after some time. Further, the costs of producing services are difficult to capture (Ammons, 1992; Ganley and Cubbin, 1992) and negative externalities may occur out of governmental actions. Last, the theoretical ability of governments might be restricted by stakeholders.

To deal with these problems of government performance measurement, efficiency approaches have been developed, while three main measures of efficiency are dis-

[1] This approach is valid as long as the partial nature economic analysis is recognized; partial in the sense of not incorporating political, sociological and other perspectives, and within economics, partial in that it is not a general equilibrium analysis.

tinguished: allocative, technical and dynamic efficiency (Dollery and Wallis, 2001). In this study the technical efficiency measurement is used. In case the Decision Making Units (DMUs) are local governments, the technical efficiency measures the success in public goods provision, dealing with a given set of regional production inputs as e.g. the budget, the available land or the available human capital[2]. Different methods are applied to measure technical efficiency (SFA, DEA, FDH). In accordance with the literature dealing with the measurement of local government performance (Balaguer-Coll et al., 2007; Charnes et al., 1989; Cook et al., 1990; Ganley and Cubbin, 1992), we consider the DEA to be appropriate. A discussion of the methodologies and reasons for the chosen approach are described in detail in section 4.1. Anyhow, at this point it is to emphasize that our calculation of a government performance measure is independent from the structural funds' explanatory variables. By this approach endogeneity problems can be avoided.

The existence of spatial dependency would lead to biased estimation results in the investigation of the SAPARD-funds allocation. Intuitively it is clear that a country differs in its structural endowment with socio-economic components as well as in its landscape elements. As structural programs aim for the reduction of regional disparities and regional cohesion, it can be imagined that the regions of a country differ in the gained support. Therefore it is self-evident to use the development-status as an explanatory variable. Nevertheless it has to be controlled for the spatial structure of the funds distribution. In case test statistics give evidence that spatial dependence occurs, a spatial lagged dependent variable Wy should be included in the estimation to control for spatial autocorrelation, i.e. that neighboring regions received similar amounts. Further, a spatial lagged error-term can be included to deal with the possibility of spillovers in the error term structure. The methods are discussed in detail in section 4.2.

It has long been recognized that the success of private and public actors depends on the knowledge of the actors (Grossman and Helpman, 1990; Glaeser et al., 1992). Comprehensible, the efficiency of local governments in using local production inputs depends on knowledge, whereas knowledge comprises all cognitions and abilities that individuals use to solve problems, to make decisions and to understand incoming information (Hayek, 1945)[3]. With respect to the participation in structural programs, the success of governments and local actors in raising funds depends on knowledge and experiences as well as regarding the development plan formulation, its implementation or the co-financing management. In this study, this kind of knowledge is included by the local governments performance.

Knowledge depends on time as well as on content, i.e. it is not static but rather continually evolving (Dohse, 2001). Therefore, the magnitude of effects of knowledge on the government performance depends on one hand on the amount of knowledge already accumulated in the past, i.e. the growth rate is positively correlated with the stock of knowledge already available (Dohse, 2001; Henderson, 1997; Henderson et al., 1995). On the other hand, following contributions of the New Economic Geography the available knowledge results from an incremental growth

[2]Success means to produce maximum outputs from a given set of inputs respectively to produce a specified level of output in the cheapest possible manner.

[3]The differences in meaning of information and knowledge can be captured as the use of information is subconscious whereas knowledge can be used consciously as well as subconsciously (Hayek, 1945). The differentiation in explicit and tacit knowledge has therefore been established: explicit knowledge can be communicated and tacit knowledge is often used unconsciously and cannot easily be made subject of verbal communication.

that occurs from learning by doing as well as from interaction with other actors (von Hippel, 1988, 1994; Mariotti et al., 2010). Several studies indicate knowledge flows between private and/or public institutions, respectively local governments (Jaffe et al., 1993; Glaeser et al., 1992; Henderson, 1997; Rosenthal and Strange, 2003; Anselin and Rey, 1997) whereas sectors with a heavy reliance on knowledge are often more sensitive to knowledge spillovers (Audretsch and Stephan, 1996) and a region with relatively low productivity/government performance might have a higher incentive to accumulate and use the gain in knowledge efficiently (Brezis et al., 1993). However, knowledge in dealing with the structural program management might circulate and imply a gain of knowledge for other agencies. It appears plausible that beyond a direct gain in knowledge due to spillover, the transmitted knowledge can also increase the incentive to participate in a structural program.

The dispersion of knowledge can occur between individuals and in a spatial dimension (Hayek, 1945). Spatial proximity enhances the communication of ideas experience and of knowledge spillovers (Caniels and Verspagen, 2001; Acs et al., 1992; Jaffe et al., 1993; Glaeser et al., 1992; Henderson, 1997; Freeman, 1991); as knowledge can be verbally communicated, not only the knowledge available to the individual decision maker but also the social network of interpersonal communication, the knowledge diffuses, is of importance. The implicit assumption of costless communication (Grossman and Helpman, 1990) might imply that distance does not play a role - but especially in relation to social networks, a higher contact frequency and closer network relations have a positive influence on joining experiences and to give, respectively ask for advice.

But, although proximity is important for generating knowledge spillovers it is not sufficient as proximity does not necessarily imply interaction and interaction does not necessarily mean positive spillovers. Investigation of firm agglomerations show that they may absorb knowledge but they may also lose it (Mariotti et al., 2010; Alsleben, 2005).

The use of an adequate technique to model the spillover effects is therefore indispensable. Regarding the above mentioned importance of spatial proximity a spatial econometric approach is suitable. The spatial Durbin model applied here is considered as superior in a wide number of applied situations. Its formulation will be discussed in detail in section 4.2.2, but to make the idea more available it is outlined in equation (Eq):1.

$$y = \alpha\iota_n + \rho W y + X\beta + W X\theta + \epsilon \qquad (1)$$
$$\epsilon \sim N(0, \sigma^2 I_n)$$

where y is the dependent variable vector, α and ι_n represent the intercept and associated coefficient, X is the explanatory variables matrix, β the associated coefficient vector and σ^2 the scalar noise parameter vector. All these listed components are identical to the conventional ordinary least squares (OLS) model. The spatial Durbin model refines the OLS model by including two sorts of spatial relation ships. Wy is a spatial lag of the dependent variable and represents a weighted average of the y-values of neighboring regions. The same applies for a spatial lag of explanatory variables WX. It contains weighted averages of the explanatory values from neighboring regions. The extended regression relationship directly takes into account values of neighboring observations and excels other spatial econometric approaches dealing only with a spatial lag of the dependent variable or of the error term. Therefore this type of model has an advantage in modeling situations involving possible spillovers.

We reasoned that the SAPARD payments and the government performance are not independent, but spatially dependent, i.e. the SAPARD payments a region receives are similar to those of neighboring regions. Further the local government performance of a region has an impact on the availability to absorb structural spendings. In accordance to knowledge being the base of a well performing government and its 'transferable-character', the funding of a region can also depend on knowledge spillovers from neighboring regions. The spatial Durbin model allows to clarify the own-region direct response and indirect spillover response. If y is the amount of SAPARD payments a regions receives, the spatial lag vector Wy represents a weighted average of neighboring SAPARD funds received. The explanatory variable X contains among others the government performance for each region. Consequently the matrix WX contains a weighted average of neighboring government performance levels. The government performance g of a region i x_{ig} can have a direct impact on the SAPARD-payments of region i y_i as well as an indirect (spatial spillover) effect on the SAPARD-payments of a neighboring region j y_j $(j \neq i)$. It is thus possible to quantify the own-region impact arising from government performance as well as spillover impacts on neighboring regions.

3 Data and descriptive statistics

3.1 Structural funding: Using the example of SAPARD

SAPARD, the Special Accession Program for Agriculture and Rural Development was established for the rural development of ten candidate countries of eastern and central Europe as a preaccession assistance. SAPARD was established in 1999 on the basis of proposals within the Agenda 2000 for the period 2000-2006 and was characterized by three priorities and by 15 eligible measures. Its general aim was to assist these countries with the structural adjustment of their agricultural sectors and rural areas, as well as with the implementation of the acquis communautaire concerning the Common Agricultural Policy and related legislation. In addition, the implementation of numerous small scale rural development projects was enforced. For improvement and guidance of program implementation a multi-annual programming approach with priority setting and continuous monitoring and evaluation was introduced. Basis of the financial allocation were the farming population, the agricultural area, the gross domestic product and the specific territorial situation (European Commission, 1999b).

Comparable to other structural funds the implementation and functioning of SAPARD was based on four principles: concentration, programming, partnership and additionality. Regarding the principle of subsidiarity the relations of the Commission and the member states were governed. Because of its decentralized management with implementing agencies in the beneficiary countries, SAPARD was conspicuous in comparison with other pre-accession instruments. Institutions were allowed to acquire the responsibility for program management and to build internal expertise and capacity to implement, monitor, and evaluate programs. This decentralization allowed to support small projects which guaranteed the share of local contracts to exceed the share of international public invitations. For the enhancement of induced positive regional effects a dualism of measures and regional investments took place. Furthermore, the decentralization implicated that the European Commission was not involved in the management of SAPARD in the beneficiary countries, apart from project ex-post controls: Ex-ante and mid-term evaluations were in responsibility of the program managing and payment authority (European Commission, 1999a).

SAPARD was co-financed, i.e. the minimum requirement for participation of the new member-states accounted for 25%. The organization was bilateral. A Multi Annual Financial Agreement (MAFA) and Annual Financial Agreements (AFA) had to be arranged, whereas the MAFA laid down the framework for co-operation and included the provisions for delegating the management of the programs to the applicant countries. Also financial control rules, monitoring and evaluation requirements and rules for the coordination with other instruments were recognized emphasizing the importance of the local agencies with respect to successful project participation.

The sole responsibility for selecting and managing projects, arranging finances and carrying out controls reflects the importance of local institutions regarding successful implementation of SAPARD. Since the partnership principle was increasingly pursued, meaning to include and involve regional and local authorities as well as economic and social partners at all stages, the local authorities gained in importance. Apart from coordination, they could assist with the development plan formulation, a pre-condition of program participation. Because of these program characteristics, the investigation of government performance and related knowledge spillovers as determinants of the SAPARD funds distribution is essential.

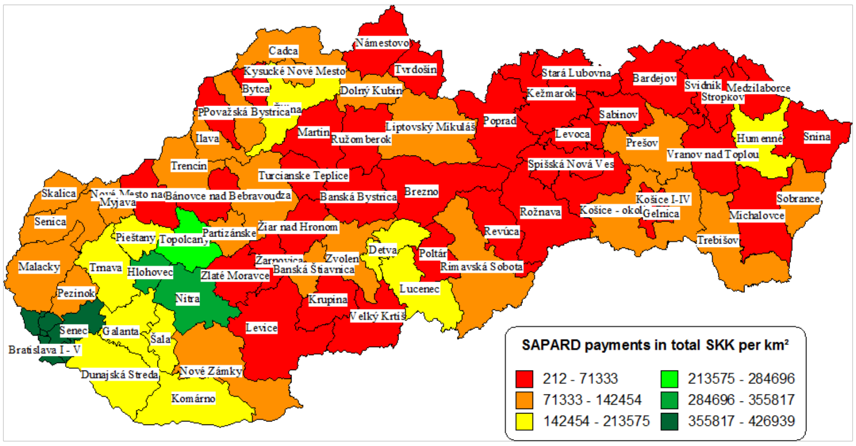
3.2 SAPARD in Slovakia

In this study Slovakia, as one of the new member states, has been chosen as object of investigation, regarding 72 LAU 1 level regions, called ‘okres’. During the period 2000-2006, SAPARD had a useable financial support from the Community budget amounting to over half a billion Euro (€) per year (European Commission, 2009). In case of Slovakia 947 programs have been accredited of which 905 have been realized. Around 4.617 million Slovakian Korunas (SKK) (112 million €) have been allocated, whereas the distribution of SAPARD-funding between the Slovakian regions differs clearly: The highest total amount was allocated in case of Nitra i.e. 6.2 million €, whereas the lowest i.e. 2600 € was spent for Poltar. The distribution per population differs from 0.11 € per capita in Poltar to 65.46 € per capita in Detva.

In several regions (average LAU 1 region, population 75000, 681 km^2), the allocated funds from the SAPARD program were for some measures negligible for several years. Therefore the estimations are based on the total amount of allocated SAPARD payments per year and do not distinguish the single measures. The estimations refer to the years 2002-2004, whereas the time period is related to the phase the majority of SAPARD payments took place. The intensity of the program support can be measured using various indicators, e.g. total per region, per capita or per km^2. While all of these indicators have advantages as well as disadvantages, we decided to relate the payments per km^2 to avoid a bias caused by the available space as the main focus of the program regards agricultural activities.

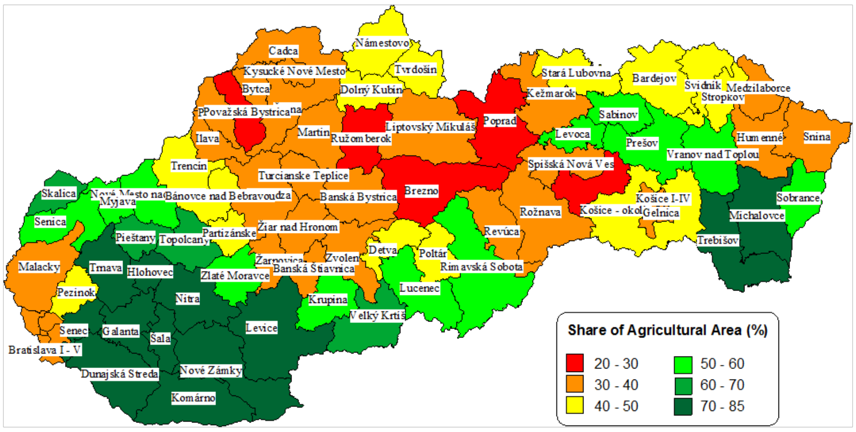
The allocation of the SAPARD payments clearly varies across regions (figure 1). In general the farming population, the agricultural area, the gross domestic product and the specific territorial situation served as basis of the financial allocation of SAPARD. In case of Slovakia the measures M1 (investment in agricultural hold-

Figure 1: SAPARD payments in total SKK per km^2



ings), M2 (improving the processing and marketing of agricultural and fishery production), M4 (development and diversification of economic activities) and M7 (land improvement and re-parceling) received the highest funding amounts. But regional development indicators such as the agricultural area or the farming population cannot explain the variances in the SAPARD funding distribution: Moreover, beyond a clearly differing regional distribution of the agricultural areas (figure 2), correlations of -0.329 and 0.526 between the SAPARD payments and the agricultural sector share, respectively the agricultural area indicate a lack of explanation. Thus, other political economy factors might have determined the access to financial support of SAPARD.

Figure 2: Share of area used for agriculture (%)



3.3 Data and descriptive statistics

Different determinants of the SAPARD funding are considerable: with respect to the payment shares of the single measures and the program design, agricultural and local governmental structures as well as different socio-economic measures were recognized as explanatory variables in the investigations. The agricultural structure was represented by the economic sector share of the agricultural sector (Agsec) and by the share of area used for agriculture (Agrarea).

Further determinants of funds distribution might be the performance of managerial-administrative institutions at both program and project level and the public and private co-financing situation. Performance becomes obvious through preparation of acceptable plans, programs, and projects in due time, and the way of deciding on programs and projects. Furthermore, coordination among the principal partners and the administrative agency and reporting work which is required by the Commission are tasks to manage as well as to finance and to supervise the implementation. The co-financing management with planning and guarantying national contributions in multi-annual budgets, and collection of these contributions from several partners are further tasks of the program authorities. As concerns private co-financing, local agencies can be helpful to identify necessary financial resources in order to cover the amounts required. Regarding this importance of local agencies, the local governmental structures are included twofold: On one hand, by the number of agencies per population (Adm), whereas a high density is perceived as helpful for development plan formulation, on the other hand by the technical efficiency of local governments (Govperf) with respect to total implementation and organization.

As a socio-economic variable the average monthly income in Euro (Inc) is included in the investigations as a development indicator; further it is conceivable that it is a proxy for the better management of co-financing. Further the mean age (Mage) of the inhabitants is chosen because young habitants might be more innovative in participating in structural programs. Otherwise older ones are more closely connected to their home region and have a higher planning dependability. The endowment with spare time facilities (Spartm) is taken as a form of social capital: A supporting character for plan formulation as well as for gaining partnerships and co-financing management is assumed. The derived quality of life measure (QL) is recognized with respect to the general purpose of structural programs to enhance the quality of life in lagging behind regions. Table (tab) 1 presents the summary statistics of the endogenous and exogenous variables included in our investigations (regarding the mean values of the investigation-period 2002-2004).

Table 1: Summary statistics

Variable	**Variable Description**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Sap(km^2)	SAPARD-funding per km^2	32761.914	48308.977	0	298101.469
Inc	Average monthly income in Euro	223.361	32.728	166.213	352.959
Adm	Administrative Units per population	0.545	0.337	0.098	1.589
Spartm	Spare-time facilities per km^2	0.004	0.001	0.002	0.010
Govperf	Government Performance	0.884	0.124	0.587	1.000
Mage	Regional mean age of habitants	27.369	1.367	22.908	29.453
QL	Regional quality of life	2.843	1.055	1.902	8.643
Agsec	Economic sector share: Agriculture	0.069	0.042	0.006	0.187
Agarea	Area used by agriculture	0.005	0.002	0.001	0.011

4 The econometric estimation

In this section methodologies to receive a local government performance measurement and to test for spatial dependencies and knowledge spillovers are introduced. First of all the measurement of government performance and regional quality of life is presented. Investigations of the differences in SAPARD-funding are conducted in three steps. First, it is generally tested for explanatory variables using cross-section data. The explanatory variables represent the average regional endowment of the years 2002-2004. The dependent variable is the total amount of SAPARD payments a region has received during this time. The explanatory content of the government performance variable attracts particularly interest. A panel data approach is used to analyze the explanatory power of variables over time. A random effects generalized least squares (GLS) model is estimated as well as a random effects tobit model[4]. The tobit model has been chosen to ensure consistency of the results because some regions did not receive payments in some years. The tobit model censors these observations.

Second, to take care of biased results caused by neglected spatial dependencies, the SAPARD-payments are controlled for spatial correlation. Spatial autocorrelation in the spatial autoregressive model is reflected in the error term and the lagged item of the dependent variable. We test both, spatial error as well as spatial lag dependencies, regarding the average regional endowment and the development of the funding over time. Third, knowledge spillovers are tested, applying a spatial econometric approach as well. These estimations are based on the the results of step one and two. In contrast to the previous estimations, the dependent as well as the independent variables are spatially lagged. A selection of variables (Inc, Spartm and Govperf) is tested for direct and neighboring, i.e. indirect or spillover effects. The selection of explanatory variables is explained by the general possibility of a spillover to take place, i.e. knowledge is transferable as is income or social capital in contrast to agricultural land or the agricultural structure. The spillover possibility in case of social capital alludes to relations to persons living outside the region.

4.1 Government Performance and Quality of Life

Understanding local politics basically as the provision of public services, government performance can be interpreted as the technical efficiency of local public goods production. Different methodologies exist to measure technical efficiency (e.g. SFA, DEA, FDH). We chose the Data Envelopment Analysis (DEA) as appropriate because of different reasons. In comparison to parametric approaches like the SFA (Stochastic Frontier Analysis), neither a priori assumptions regarding the production-function nor regression-analytical approaches are necessary. Instead, using a linear programming approach the production frontier is received, determined by the efficient units. Furthermore, multidimensional relationships among several inputs and outputs can be used (Zhu, 2001). Since the DEA is a deterministic approach it does not account for the possibility of stochastic influences. That is a disadvantage of the chosen methodology. All deviations from the estimated production frontier are interpreted as inefficiencies. Nevertheless, the separate calculation of a government performance measure allows to investigate the relationship between funding allocation and government performance without endogeneity bias which could otherwise be expected.

In the DEA, an efficient region has production inputs comparable to other regions but higher efficiency using those resources to produce greater outcomes. To the contrary, an efficient local government may similarly be viewed as having comparable public goods as outputs, but generally produces those levels of outputs with fewer resources. DEA models have been applied differently in literature (Cook et al.,

[4]The Hausman's specification test proves that a random effects estimation is appropriate.

1990; Rouse et al., 1995; Worthington, 1999); among others for analyzing the efficiency terms of economic development of cities (Charnes et al., 1989, 1994) and the efficiency of local governments (Balaguer-Coll et al., 2007). Applications of the DEA can be found in Dollery and Wallis (2001). Emrouznejad et al. (2008) present a list of DEA research covering theoretical developments as well as "real-world" applications.

In this study, production inputs are factors local governments are able to influence as well as the given local conditions; outputs are thereby produced public goods and related amenities. The number of inputs and outputs is chosen according to Dyson et al. (2001). It has been taken care of non-negativity as well as for changing the direction of undesirable outcomes. The relative efficiency measure is scaled so that it ranges between [0,1]. Each Decision Making Unit (DMU) j has multiple inputs $x_{i,j}$ and multiple outputs $y_{k,j}$; u and v are weights (Eq:2).

$$Efficiency = \frac{\sum_k u_k y_{k,j}}{\sum_i v_i x_{i,j}} \tag{2}$$

By this each DMU j_0 is allowed to set its own weights. The optimization problem (Eq:3) is given as the efficiency of DMU j_0 is maximized subject to the condition that all efficiencies of other DMU's remain less than or equal to 1. By this the denominator is fixed to a constant value, e.g. 1.0, which can be interpreted as setting a constraint on the weights v_i (Kalvelagen, 2004):

$$\begin{aligned} \max u, v \sum{}_k u_k y_{k,j_0} \\ s.t. \sum{}_i v_i x_{i,j_0} = 1 \\ \sum_k u_k y_{k,j} \leq \sum_i v_i x_{i,j} \forall j \\ u_k, v_i \geq 0 \end{aligned} \tag{3}$$

The DMUs are the 72 (LAU1) regions in Slovakia. As DEA inputs income, employment, agricultural area as well as forest- and water-area per total area, the share of built-up area and unemployment payments per unemployed as a proxy for the regional budget conditions are recognized. In order to receive a more complex description of the production outcomes, the methodology of the principal component analysis is applied to reduce the multitude of outcome variables and to classify them to significant public-good variables by detecting structure in their relationships. Thus, the basic and daily technical infrastructure, the social infrastructure, the endowment with city-life amenities, the economic structure and the environmental quality were received as outputs.

Because the DEA has in recent years also been applied to obtain synthetic indicators of well-being and quality of life (Somarriba and Pena, 2009; Raab et al., 2000; Murias et al., 2006; Hashimoto and Cohn, 1997; Despotis, 2004; Marshall and Shortle, 2005; Zhu, 2001) we followed these approaches and used the received output weights u and produced public goods Y to calculate a quality of life index (Eq:4). However, applications in this field of investigation are still few and far between.

$$LQ = \frac{\sum_j u_j Y_j}{\sum_j^m u_j} \tag{4}$$

4.2 Spatial Econometric Approach

Beside socio-economic components, quality of life and local government performance, the spatial location of a region might be a further determinant of the structural funds allocation. It is commonly observed that sample data collected for regions or points which are ordered in space or in space and time are not independent, but rather spatially dependent (LeSage, 2008). The spatial dependence exists as a functional relationship between occurrences in one region and occurrences elsewhere, whereas two general forms of dependencies can be found: One obvious cause is the spatial spillover in measurement errors. The second factor follows from the importance of space as an element in structuring explanations of human behavior; i.e. location and distance matter and result in a variety of interdependencies in space and time (Anselin, 1988). Following our considerations as outlined at the beginning, the amount of raised SAPARD payments might therefore depend on the region itself as well as (in part) on the neighboring regions, on an agglomeration of similar characteristics, respectively. Moreover, because the success in raising SAPARD funds depends on the performance in program implementation, this ability is determined by accumulated knowledge at the beginning of the program. But also spillovers from other regions might be decisive. Governments which gained experiences in fund-raising are likely to pass this knowledge to agents of neighboring regions. The existence of spatial hierarchical relationships, spatial spillovers and other types of spatial interactivity are an intuitive motivation for this.

Different possibilities exist to deal with spatial dependencies. Common is the idea that in a cross-sectional setting with N observations, there is insufficient information to estimate the $N \times N$ covariance matrix directly from the data. In general it will be necessary to impose a structure on the covariance. Therefore a $N \times N$ spatial weights matrix W is included in the estimation approaches. The elements of the weights matrix quantify the connections between regions and are based on the geographic arrangement of the observations, or the contiguity. The specification of the spatial weights can be differently managed, e.g. weights are non-zero in case two locations share a common boundary, or in case they are within a given distance of each other. In this study, a first order contiguity matrix is used, containing zeros on the main diagonal, rows that contain zeros in positions associated with non-contiguous regions and ones in positions reflecting neighboring units that are (first-order) contiguous. Contiguous is defined as sharing a common okres-boundary. The matrix used in the estimations is transformed. It is converted to have row-sums of unity. This ensures that variables when they are spatially lagged, represent the average value of neighboring regions.

4.2.1 Spatial dependencies

From the different spatial econometric models described in the respective literature, in this study a spatial lag, respectively spatial mixed autoregressive model and the spatial error model are applied as well as a combination of both, meaning a spatial lag model with a spatial regressive error term[5]. A general impression if spatial dependence occurs can be derived from spatial statistic means (e.g. Moran's Index (Moran's I), Geary's Index (Geary's C) and Getis's G or O). The purpose of all these indexes is very similar. The index most often encountered - Moran's I,

[5]In regard to spillovers in the explanatory variables, the spatial Durbin model is discussed in section 4.2.2.

is structured like the Pearson's product-moment statistic. A positive spatial autocorrelation means that neighboring areas have similar rates which is an indicator for spatial clustering. In comparison to autocorrelation which is about proximity in time, spatial autocorrelation is about proximity in space and therefore more complex because of a two-dimensional and bi-directional correlation. In Eq:5 the definition of Moran's I is given with w_{ij} as the weight, $w_{ij} = 1$ if locations i and j are adjacent and zero otherwise ($w_{ii} = 0$, an region is not adjacent to itself). y_i and $\overline{y}$ are the variable in the ith location and the mean of the variable, respectively; n is is the total number of observations and I is used to test hypotheses concerning similarity. A positive Moran's I indicates similar rates of nearby areas whereas Moran's I will be negative in case the rates are dissimilar[6].

$$I = \frac{n}{\sum_i^n \sum_j^n} * \frac{\sum_i^n \sum_j^n w_{ij}(y_i - \overline{y})(y_j - \overline{y})}{\sum_i^n (y_i - \overline{y})^2} \tag{5}$$

From the global Moran's I the Moran's scatterplot can be derived directly. It is a graphical tool for detecting local spatial association. If a row standardized weights matrix is used in Eq:5 the first term will be 1. Therefore, I can be re-written as Eq:6, whereas $\sum_j^n w_{ij}(y_j - \overline{y})$ is the so-called 'spatial lag' of location i. Because I is formally equivalent to a regression coefficient in a regression of a locations spatial lag on itself, the Moran's I can be visualized in a scatterplot of locations spatial lag and itself. Moran's I is the slope of the regression line.

$$I = \frac{\sum_i^n \sum_j^n w_{ij}(y_i - \overline{y})(y_j - \overline{y})}{\sum_i^n (y_i - \overline{y})^2} \tag{6}$$

If the test statistics give evidence for the occurrence of spatial dependency, different forms of dependencies should be controlled. The spatial lag dependence refers to the assumption of correlated errors as occur between the dependent variables. Spatial spillover effects between observations of the dependent variable (Saavedra, 2003) can be a reason of this sort of spatial dependence. The model can be used to test if SAPARD payments of one region affect the payments of neighboring regions. Therefore, the spatial lag model (Eq:7) combines the standard regression model with a spatially lagged dependent variable, with y as the dependent variable vector, X represents the data matrix containing the explanatory variables and W is the spatial weight matrix. The estimated parameters ρ and β represent the coefficients of the spatially lagged dependent variable and the influence of the explanatory variables. With respect to the object of investigation a spatial lag vector Wy is added, reflecting the average SAPARD-payments from neighboring regions to explain variation in payments across regions. Intuitively, the SAPARD-payments of each region are related to the average payments of neighboring regions. The average strength of this relationship across the sample of regions is determined by the parameter ρ. ϵ follows a multivariate normal distribution, with zero mean and a constant scalar diagonal variance-covariance matrix $\sigma^2 I_n$.

$$\begin{gathered} y = \rho W y + X\beta + \epsilon \\ \epsilon \sim N(0, \sigma^2 I_n) \end{gathered} \tag{7}$$

[6]With respect to Li et al. (2007) the Moran's I statistic results are only used as in indicator of spatial dependence; however, it cannot be used as an estimator of the strength of spatial dependence.

Simultaneous feedback is a feature of the spatial regression model that arises from dependence relations. The model in Eq:8 (data generating process) indicates that the expected value of each observation y_i will depend on the mean value $X\beta$ plus a linear combination of values taken by neighboring observations scaled by the dependence parameter ρ. This expresses the simultaneous nature of the spatial autoregressive process. Further, in accordance to the remarks at the beginning respective differentiation of direct, indirect and total effects of spillovers regarding the spatial lagged dependent variable, this differentiation is adequate as well.

$$\begin{aligned} y = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1}\epsilon \\ \epsilon \sim N(0, \sigma^2 I_n) \end{aligned} \tag{8}$$

Another way to incorporate spatial autocorrelation in a regression model is to specify a spatial process for the disturbance terms (Anselin and Bera, 1998). In the spatial error model (Eq:9) the spatial dependencies are exhibited by the disturbances with u reflecting the spatially autocorrelated error term. The parameter λ represents the coefficient of spatially correlated errors. This form of spatial dependence may be interpreted as a nuisance in the sense that it reflects spatial autocorrelation in the measurement errors or in omitted variables. It causes a problem of inefficiency in the regression estimates, which may be avoided by increasing the sample size. Patton and McErlean (2003) contend that the consequences of ignoring spatial lag dependence are more severe than the consequences of ignoring spatial error dependence. The reason is that the former is related to theoretical considerations while the latter is related to a statistical reason (LeSage, 1997).

$$\begin{aligned} y &= X\beta + u \\ u &= \lambda W u + \epsilon \\ \epsilon &\sim N(0, \sigma^2 I_n) \end{aligned} \tag{9}$$

In case spatial dependence exists in the error structure from a spatial autoregressive model, a general version of the spatial model including a spatial lagged term and spatially correlated error structures is an appropriate approach to model this type of dependency (Eq:10). By this W_1 can equal W_2 but also different formulations can be found. With reference to LeSage and Pace (2009) we construct W_2 as W_2=W'W.

$$\begin{aligned} y &= \rho W_1 y + X\beta + u \\ u &= \lambda W_2 u + \epsilon \\ \epsilon &\sim N(0, \sigma^2 I_n) \end{aligned} \tag{10}$$

According to panel data, the spatial autoregressive as well as the spatial error model change to Eq:11 and Eq:12 (Elhorst, 2003). ϵ_t is an independently distributed error term with zero mean and variance σ^2. For both models (Eq:11 and Eq:12) it is maintained that W is constant over time and the panel is balanced. The parameter μ denotes spatial specific effects, that can be treated as fixed effects or random effects. The standard reasoning to include spatial specific effects is that they control for all space-specific time-invariant variables. Their omission could bias the estimates in a cross-sectional study (Elhorst, 2010). In the fixed effects model for each region a dummy variable is introduced. In the random effects model μ is treated as a random variable (independently and identically distributed with zero mean and variance σ^2_μ). A further assumption is that the random parameters μ and ϵ_t are independent of each other[7]. The random effects model can be tested against the fixed effects model using Hausman's specification test (Baltagi, 2005). This test can also be applied when the model is extended to include spatial error autocorrelation or a spatially lagged dependent variable. The data-set used in this study comprises only three years. Of course, the spatial fixed effects should only be estimated when t is sufficiently large. To decide whether the spatial lag or spatial error model is more appropriate, the Lagrange Multiplier (LM) test can be used.

$$\begin{aligned} y_t = \rho W y_t + X_t\beta + \mu + \epsilon_t \\ \epsilon_t \sim N(0, \sigma^2 I_n) \end{aligned} \tag{11}$$

$$\begin{aligned} y_t &= X_t\beta + \mu + u_t \\ u &= \lambda W u_t + \epsilon_t \\ \epsilon_t &\sim N(0, \sigma^2 I_n) \end{aligned} \tag{12}$$

4.2.2 Knowledge-Spillovers

In the models Eq:7 - Eq:12 the SAPARD payments received are explained by the average payments of the neighboring regions as well as by a set of explanatory variables. To test for occurring spillovers in the explanatory variables, the spatial autoregressive model Eq:7 is expanded to Eq:13 (spatial Durbin model), including now a spatial lag of the dependent variable (Wy) as well as of the explanatory variables (WX) (Anselin, 1988). The advantage of this model is to take values of neighboring regions for the dependent as well as the independent variables directly into account. Characteristics that determine the access to SAPARD as e.g. the government performance from neighboring regions exert an influence on received SAPARD payments of a single region. The variant given in Eq:13 allows payments for each region to depend on own-region factors from matrix X that influence funds allocation, plus the same factors averaged over the neighboring regions, WX (LeSage, 2008). We are thus able to test if the government performance, the average income and the social capital endowment of neighboring regions have an influence on the SAPARD payments a region receives; in other words if knowledge or financial spillovers take place.

$$\begin{aligned} y = \alpha\iota_n + \rho W y + X\beta + WX\theta + \epsilon \\ \epsilon_t \sim N(0, \sigma^2 I_n) \end{aligned} \tag{13}$$

In Eq:13 the spatial Durbin model is given, with y is the $n \times 1$ vector of dependent variable observations, ι_n and α represent the intercept and associated coefficient; X the $n \times k$ explanatory variable matrix with β an associated $n \times 1$ vector of

[7]The derivation of fixed effects spatial lag/error and random effects spatial lag/error models can be found in Elhorst (2010).

coefficients. σ^2 is the scalar noise variance parameter; the $n \times n$ matrix W contains information in the spatial relationship between observations. The spatial lag of the dependent variable (Wy) is a $n \times 1$ vector containing a (weighted) average of the y-values from neighboring regions. The $n \times k$ matrix WX, which is the spatial lag of the explanatory variables contains (weighted) averages of the explanatory variable values from neighboring regions (LeSage and Pace, 2010).

In case ρ unequals zero the conventional least squares interpretation of the parameter vectors in the spatial Durbin model is not valid, because the dependence expands the information set to include information from neighboring regions. Since the impact of changes in an explanatory variable differs over all regions, scalar summary measures are applied which average these impacts across all units (Pace and LeSage, 2006; LeSage, 2008). These are the average direct, the average indirect and the average total effects. The direct effect is related to individual regions. It provides an averaged measure over all regions, capturing the impact arising from changes in one region on the dependent variable, e.g. the impact of an increased government performance of region i on the absorbed SAPARD funds of region i. Feedback effects that arise from the changed government performance of region i on the SAPARD payments of neighboring regions are also taken into account by this measure. The indirect effect corresponds to the impact on raised funds, occurring from neighboring regions. This means in case all neighboring regions get a higher government performance (get more knowledge to deal successful with structural programs), the indirect effect measures the impact on the raised SAPARD funds on an individual region (on average). The average total effect is the sum of the direct and the indirect effect. Two interpretations are feasible. First, in case all regions receive a gain in knowledge/government performance, it measures the average total impact on received SAPARD funds of the typical region. Second, the total effects measure the total cumulative impact arising from a region j that gains in knowledge on the amount of SAPARD funds of all regions, averaged over all regions. The spatial Durbin model can also be used with panel data. The estimation procedure is comparable to the described spatial lag and spatial error panel model (see section 4.2.1). Therefore, a spatial Durbin model with spatial fixed effects takes the form (Eq:14):

$$y_t = \rho W y_t + \gamma W X_t + X_t \beta + \mu + \epsilon_t \qquad (14)$$
$$\epsilon_t \sim N(0, \sigma^2 I_n)$$

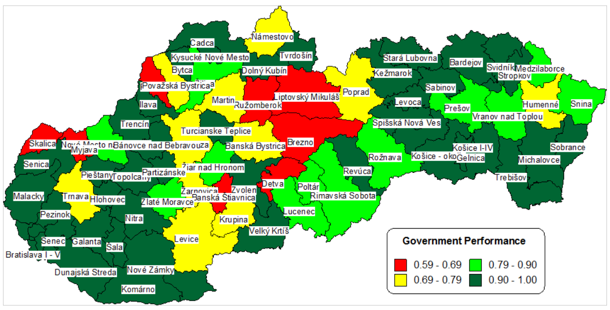
5 Estimation Results

In this section the estimation results of measuring local government performance as well as the results of the spatial econometric models are presented. In addition to evaluate the gain in explanation base-run models are estimated. Regarding the government performance an OLS regression is estimated, recognizing all introduced explanatory variables apart from the government performance. With respect to the spatial models, base-run models are estimated as well regarding both, cross-section as well as panel data.

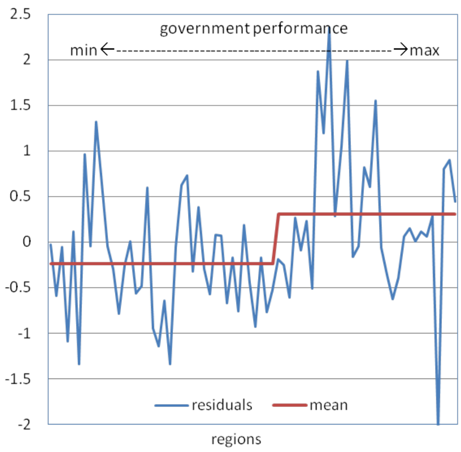
5.1 Government Performance

The estimation of the DEA yields technical effciency measures for the years 2002, 2003 and 2004 as well as an average technical efficiency measure using the average endowment of the years 2002-2004 as production inputs and outputs. The resulting technical efficiency measures of the DEA are illustrated in figure 3, regarding the average regional endowment. The regional distribution shows clear regional differences in government performance. Further, the residual plot indicates a better model fit by including the government performance in the explanatory variable setting. This is illustrated by the residuals distribution of the base-run model, sorted due to the estimated technical efficiency values. In addition two mean values of the residuals are included, capturing in each case half the number of regions. The sum of the residuals equals almost zero. Just as many high as low misses are given. The sign of the residual indicates whether the guess was too high (positive) or too low (negative). In figure 3 a concentration of too high and too low values is conspicuous. This means in case government performance is not included in explanatory variables, the low-performing regions tend to underestimate whereas well-performing regions have a tendency to overestimate. This indicates clearly, that it should be controlled for the local government performance.

Figure 3: Government Performance (average: 2002-2004)



Goverperf: Regional Distribution

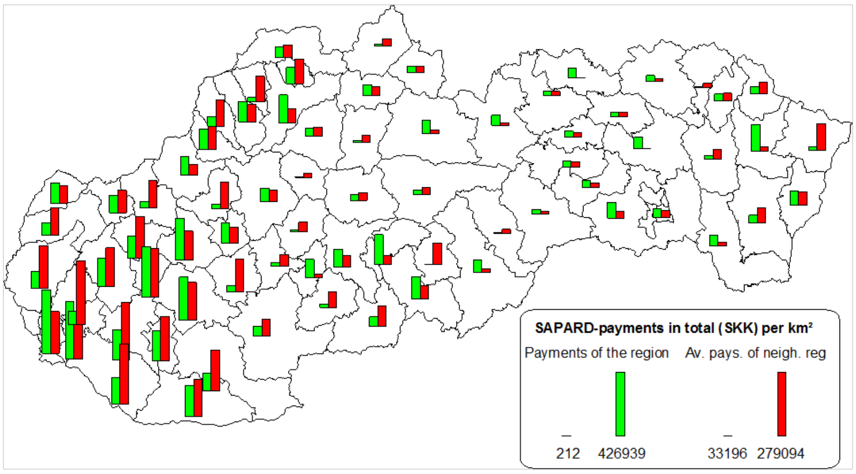


Residual Plot

5.2 Spatial Dependencies

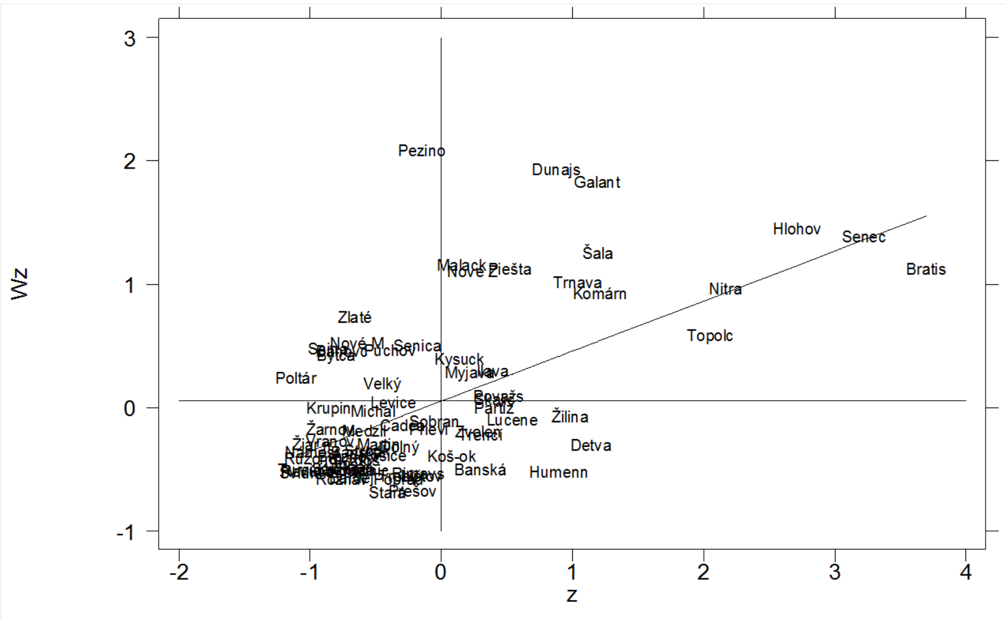
Spatial autocorrelation occurs if the value at any one point in space is dependent on values at the surrounding points; therefore the arrangement of values is not just random (Wang, 2006). In case similar values tend to be near one another, positive spatial correlation occurs; negative spatial correlation means that different values tend to be near one another. Considering the possibility of spatial correlations in the distribution of SAPARD-payments in figure 4 the possibility of an occurring spatial lag is visualized by a spatial lag bar chart. Therefore the value of one region i is compared to the weighted average of the neighboring regions (x_i relative to $(Wx)_i$). Figure 4 shows for most of the regions similar amounts of SAPARD payments compared to the payments the neighboring regions received, i.e. spatial autocorrelation is likely to occur.

Figure 4: Spatial lag bar chart



For a general impression of spatial autocorrelation Moran's I is calculated regarding the total received SAPARD payments per km^2 of the years 2002 - 2004. The Moran's I statistic indicates a significant degree of spatial clustering (correlation among values of neighboring units), unlikely to have occurred by chance (Anselin, 1999). In figure 5 the Moran's I scatterplot is given. The scatter-plot figure is centered on the mean with the axes drawn so that the four quadrants are clearly shown. Each quadrant corresponds to a different type of spatial autocorrelation: high-high and low-low for positive spatial autocorrelation; low-high and high-low for negative spatial autocorrelation. The positive slope of 0.405 represents the existence of spatial autocorrelation, whereas the concentration of data points in the third quadrant indicates association of low-low received spendings of neighboring regions.

Figure 5: Moran scatterplot: SAPARD payments total per km^2, Slovakian okres



(Moran's I = 0.405)

The global Moran's I (see figure 7) can be decomposed into local indicators of spatial association, which identify local clusters of units with similar values (see Eq:6) (Anselin, 1999). The received positive local spatial autocorrelation is typically referred to as spatial clusters, while the high-low and low-high locations (negative local spatial autocorrelation) are termed spatial outliers. Outliers are single locations by definition, this is not the case for clusters. In figure 6 the spatial clustering is illustrated.

Figure 6: Spatial Cluster

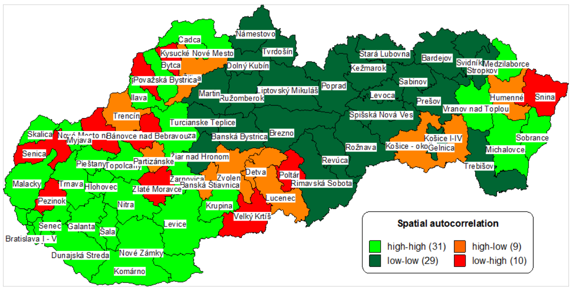


Figure 7: Moran's I Statistic 2002-2004

Year	I	sd(I)	z	p-value
2002	-0.019	0.068	-0.074	0.471
2003	0.240***	0.069	3.673	0.000
2004	0.301***	0.070	4.480	0.000

The results shown above reveal the existence of spatial correlation in the funding distribution. Because the Moran's I does not show the strength of the spatial relationship, further spatial econometric models are estimated. First, we estimated the spatial-lag, -error and generalized spatial model, using the average regional endowment of the years 2002-2004 as explanatory variables (tab: 2). The total received SAPARD payment per km^2 is the dependent variable. For comparison the OLS results are listed in the appendix (fig: 9). In tab: 3 the direct, indirect and total effects of the spatial lag model are given.

The three models give similar results for the significances as well as for the directions of estimated coefficients (tab: 2). The average income and the government performance exhibit a clear positive significant effect on the SAPARD allocation. The idea that the government performance is a significant determinant of the structural funding distribution is therefore reinforced as well as the assumption that a higher average income results in a better co-financing management. The mean age and the share of land used by agriculture lead to a higher payment allocation, although not significantly in all three models. The positive effect of the agricultural used area is an expected result as it is in line with the general SAPARD program objectives to support agricultural holdings and to improve the processing and marketing of agricultural production. Regarding the significant influence of the mean age, positive correlations with the average income could be an explanation; but this is not the case. Rather, a higher age might represent a higher identification with the region and a better endowment with confiding social relations. The development plan formulation and co-financing might be more easily managed and a higher incentive to participate in the SAPARD program might occur from a clearer and more settled individual planning.

The results also indicate that the dependent variable exhibits strong spatial dependence as the effect of ρ on the spatial lagged variable is significant. Therefore, OLS estimates are biased and inconsistent; furthermore taking spatial variation into account improves the fit of the model, raising the R-squared statistic for the spatial models. The derivation of direct, indirect and total effects (tab: 3) shows that the average income and the government performance are the main drivers of the funding allocation. Conspicuously, the direct effects are more important than the indirect effects. The income is more decisive for the funds allocation than the government performance. Regarding the total effects, the impact of the average income amounts to nearly 120% of the government performance effect.

Table 2: Estimation results - spatial models: average regional endowment (2002-2004)

	Spatial autoregressive model		Spatial error model		General spatial model	
Variable	Coeff (t-stat)	z-prob	Coeff (t-stat)	z-prob	Coeff (t-stat)	z-prob
constant	-1.839**	0.022	-1.686*	0.054	-1.938***	0.007
	(-2.291)		(-1.929)		(-2.697)	
Inc	0.328**	0.02	0.388***	0.009	0.301**	0.018
	(2.321)		(2.614)		(2.363)	
Adm	-0.088	0.504	-0.138	0.323	-0.07	0.553
	(-0.668)		(-0.989)		(-0.594)	
Spatm	0.018	0.875	0.018	0.885	0.015	0.887
	(0.157)		(0.144)		(0.142)	
Govperf	0.250**	0.033	0.325**	0.01	0.250**	0.016
	(2.128)		(2.587)		(2.418)	
Mage	0.162*	0.096	0.257**	0.015	0.13	0.11
	(1.667)		(2.439)		(1.596)	
QL	0.116	0.425	0.021	0.887	0.118	0.379
	(0.798)		(0.142)		(0.879)	
Agsec	-0.254	0.268	-0.361	0.143	-0.172	0.395
	(-1.107)		(-1.465)		(-0.850)	
Agarea	0.329	0.137	0.401*	0.092	0.27	0.171
	(1.488)		(1.683)		(1.369)	
ρ	0.067***	0.004			0.484***	0
	(2.892)				(5.96)	
λ			0.158	0.338	-0.08	0.67
			(0.958)		(-0.426)	
R-squared	0.468		0.461		0.596	
Rbar-squared	0.4		0.392		0.545	
sigma2	0.479		0.532		0.399	
log-likelihood	-51.562		-54.7		-46.129	

**** p < 0.01; ** p < 0.05; * p < 0.10*

The consideration that administrative units as well as social relations have a supporting character to receive SAPARD payments cannot be approved by this estimation setting. The same applies for the regional quality of life and the agricultural sector. The Lagrange Multiplier error test for spatial correlation in the residuals indicates that the least squares residuals do not exhibit spatial correlation. Therefore the insignificant estimate for the parameter λ in the spatial error model is consistent. The results of the general model show significant results of ρ whereas λ is insignificant.

As the majority of SAPARD payments took place during the years 2002 to 2004, it seems adequate to use a panel data approach in comparison to the average regional endowment discussed before. The application of Hausman's specification test shows that a random-effects model is better suited than a fixed-effects model. The results of a simple random-effects model without spatial effects are shown in the appendix (tab: 8). Due to the fact that in some years some regions did not receive support by SAPARD, a random effects tobit model is estimated in addition[8]. The results are also listed in the appendix (tab: 8). Due to spatial dependencies in tab: 4 a spatially lagged dependent variable is included. Three different estimations are given: a model without fixed effects, with time period fixed effects and with spatial

[8]The tobit model shows nearly no differences compared to the GLS estimation results.

Table 3: Estimation results - spatial models: direct, indirect and total effects

	Spatial autoregressive model								
	direct			indirect			total		
Variable	Coeff	t-stat	t-prob	Coeff	t-stat	t-prob	Coeff	t-stat	t-prob
Inc	0.337*	1.877	0.065	0.274**	2.023	0.047	0.611**	2.258	0.027
Adm	-0.072	-0.565	0.574	-0.057	-0.671	0.504	-0.129	-0.559	0.578
Spatm	0.017	0.140	0.889	0.020	0.190	0.850	0.037	0.171	0.865
Govperf	0.276*	1.784	0.079	0.226*	1.845	0.069	0.502**	2.200	0.031
Mage	0.143	1.366	0.176	0.112	1.602	0.114	0.255	1.594	0.115
QL	0.119	0.837	0.406	0.094	0.760	0.450	0.213	0.832	0.408
Agsec	-0.180	-0.761	0.449	-0.148	-1.036	0.304	-0.329	-0.804	0.424
Agarea	0.288	1.342	0.184	0.235	1.336	0.186	0.523	1.319	0.191

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

random effects. The Hausman test gives evidence that again a random-effects model is more appropriate. The results do not differ significantly from cross-sectional ones, but the significances change for the better. Further, it is tested for spatial error autocorrelation (see tab: 9 in the appendix). In the panel setting both, the spatial lag as well as the spatial error parameter stand out as significant. The high significant estimate for the spatially lagged variable indicates that the received SAPARD payments of a region clearly depend on the receipts of the neighboring regions.

The estimation results of the panel regression models with the spatially lagged dependent variable show significant results for the income, the regional social capital endowment, the government performance and the variables related to agriculture. The positive influence of the government performance supports once more our considerations that efficient working government agencies are helpful in project participation and successful in raising financial means. The management of co-financing is easier the more higher the average income. The negative direction of the agricultural sector variable (Agsec) is hardly to explain. Presumably a region with a high agricultural share in the economy sector structure represents lagging behind regions that cannot manage the co-financing and are less innovative in taking part in structural programs than regions with a differing sectoral structure.

Even if insignificant the negative result of the quality of life measure is remarkable. It indicates that the general aim of structural programs to enhance the quality of life is realized. The more the region lags behind in its quality of life compared to other regions, the better the structural support. Comparing the log-likelihood values and R-squared statistics, both spatial models fit better than the simple regression and tobit regression models do. Therefore, the importance to recognize spatial dependencies in analyzing structural spending is reinforced. Additionally, the spatial autoregressive model is more suitable than the spatial error one (see tab: 9 in the appendix).

5.3 Knowledge Spillovers

So far, the main findings of the conducted estimations are positive significant impacts of the government performance and the average income. Further, the SAPARD funding is spatially correlated, i.e. the funding of a region depends on the receipts of the neighboring regions. Because the regional SAPARD payments might be determined by the government performance/management facilities of the neighboring regions, by the neighboring average income or by the neighboring social capital en-

Table 4: Spatial Panel Models

	Pooled model with spatially lagged dependent variable, no fixed effects		Pooled model with spatially lagged dependent variable, time period fixed effects		Pooled model with spatially lagged dependent variable, spatial random effects	
Variable	Coeff (t-stat)	z-prob	Coeff (t-stat)	z-prob	Coeff (t-stat)	z-prob
const	-0.818 (-1.565)	0.118			-0.824 (-1.573)	0.116
Inc	0.244*** (2.747)	0.006	0.09 (0.917)	0.359	0.247*** (2.77)	0.006
Adm	-0.02 (-0.271)	0.786	-0.11 (-1.439)	0.15	-0.02 (-0.267)	0.79
Spatm	0.179** (1.988)	0.047	0.181 (2.060)	0.039	0.179** (1.985)	0.047
Govperf	0.131* (1.810)	0.07	0.113 (1.568)	0.117	0.133* (1.827)	0.068
Mage	0.088 (1.402)	0.161	0.112* (1.845)	0.065	0.089 (1.412)	0.158
QL	-0.093 (-0.993)	0.321	-0.03 (-0.320)	0.749	-0.095 (-1.007)	0.314
Agsec	$-0.243^{\perp}$ (-1.645)	0.1	-0.181 (-1.236)	0.216	-0.245* (-1.654)	0.098
Agarea	0.235* (1.664)	0.096	0.149 (1.065)	0.287	0.236* (1.672)	0.094
ρ	0.421*** (5.698)	0	0.276*** (3.278)	0.001	0.416*** (5.596)	0
teta					0.997*** (9.775)	0
R-squared	0.415		0.443		0.416	
Rbar-squared	0.39		0.413		0.346	
sigma2	0.66		0.629		0.66	
log-likelihood	-266.155		-258.223		-266.152	

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$; $^{\perp}$ $p = 0.10$

dowment, the possibility of knowledge as well as financial and social spillovers is included in the estimations. In the spatial Durbin model the dependent variable is still the amount of SAPARD payments a region received, but as explanatory variables the average income, the government performance and the social capital indicator 'Spatm' are included. The regional endowment is recognized as well as a spatially lagged form, i.e. the average endowment of explanatory variables in the neighboring regions.

The spatial Durbin model (figure 8) demonstrates significant results for the total effects of income and government performance. A comparison of direct and indirect effects shows that the direct income effect of a region i is more decisive than the indirect effect that occurs from neighboring regions; for the government performance it is just the reverse. It has to be noted that the indirect effect of the government performance as well as of the income is positive, which suggests the existence of a spillover effect. In particular the average government performance of neighboring regions has a positive effect on the SAPARD payments allocation. The effect is nearly twice as high as the average income. This means in case all neighboring regions get more knowledge to deal successfully with structural programs, the impact on the raised SAPARD funds on an individual region on average is higher than in case the income rises for all neighboring regions. Regarding the total effects, the

Figure 8: Spatial Durbin Model

Variable	Coeff	t-stat	z-prob
const	-1.665**	-2.115	0.034
Inc	0.355***	3.238	0.001
Spatm	0.147	1.562	0.118
Govperf	0.127	1.269	0.204
W-Inc	0.121	0.693	0.488
W-Spatm	-0.296*	-1.685	0.092
W-Govperf	0.378**	2.149	0.032
rho	0.338**	2.349	0.019
R-squared		0.448	
Rbar-squared		0.397	
log-likelihood		-52.345	

Spatial Cluster

Variable	Coeff	t-stat	z-prob
		direct	
Inc	0.375***	3.563	0.001
Spatm	0.126	1.327	0.189
Govperf	0.161	1.648	0.104
		indirect	
Inc	0.343	1.650	0.103
Spatm	-0.359	-1.361	0.178
Govperf	0.604**	2.433	0.017
		total	
Inc	0.718***	3.475	0.001
Spatm	-0.234	-0.829	0.410
Govperf	0.765***	3.056	0.003

Direct, indirect and total effects

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

government performance points out as being even more decisive than the average income. So, in case all regions receive a gain in knowledge the average total impact on the amount of received SAPARD funds of the typical region is higher than in case of an increase in income. The total effects make allowances for feedback effects, i.e. the feedbacks arising by a change in the ith regions's government performance or average income of neighboring regions in the system of spatially dependent regions. Therefore, spillovers of knowledge take place, regarding the project participation and implementation as well as financial spillovers, enhancing the co-financing management.

A clear advancement of the estimation by application of the spatial Durbin model takes place. Around 10 percent of the variation in the SAPARD payments allocation is explained by spatial dependence, because the R^2 changes from 0.345 in the least squares model to 0.448 in the spatial Durbin model. Moreover, comparing the estimation results of the SDM-model onetime with and onetime without recognition of government performance as explanatory variable, the importance of the government performance to explain differences in the SAPARD-distribution is maintained (see figure 10 in the appendix).

For investigation of the temporal relationship of spillover effects, the panel-data approach is estimated in addition. The results for the fixed- and random effects model are listed in tab: 5. Comparable to the estimation results of the spatial lag and error models, using panel data in the spatial Durbin model does not cause other directions of the estimated parameters but the significances change for the better. The direct, indirect and total effects (tab: 6) are significant for both, income and government performance. In contrast to the cross sectional setting, the total effect of the average income exceeds the effect of the government performance. It is conspicuous, that the government performance has still the highest indirect effect.

6 Conclusions

This study analyzes the regional SAPARD funding disparities at LAU1 level in Slovakia. The data used in this research are annual data collected during 2002-2004. The period of investigation is chosen with respect to the period the majority

Table 5: Spatial Panel: Spatial Durbin Model

	Pooled model with spatially lagged dependent variable, no fixed effects		Pooled model with spatially lagged dependent variable, time period fixed effects		Pooled model with spatially lagged dependent variable, spatial random effects	
Variable	Coeff (t-stat)	z-prob	Coeff (t-stat)	z-prob	Coeff (t-stat)	z-prob
constant	-1.665* (-1.685)	0.092			-0.01 (-0.174)	0.862
Inc	0.374*** (5.552)	0	0.277*** (3.720)	0	0.277*** (3.670)	0
Spatm	-0.046 (-0.815)	0.415	-0.066 (-1.171)	0.242	-0.066 (-1.152)	0.249
Govperf	0.065 (0.989)	0.323	0.059 (0.911)	0.362	0.06 (0.911)	0.362
W*Inc	-0.022 (-0.190)	0.849	0.122 (1.028)	0.304	0.12 (1.000)	0.317
W*Spatm	0.007 (0.047)	0.962	0.047 (0.321)	0.748	0.047 (0.317)	0.751
W*Govperf	0.224* (1.793)	0.073	0.267** (2.156)	0.031	0.266** (2.117)	0.034
W*dep.var.	0.443*** (6.007)	0	0.285*** (3.250)	0.001	0.290*** (3.314)	0.001
teta					0.968*** (9.713)	0
R-squared	0.409		0.430		0.251	
Rbar-squared	0.343		0.189		0.189	
sigma2	0.667		0.652		0.629	
log-likelihood	-267.884		-260.776		-260.723	

**** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$*

of SAPARD-payments' allocation took place. In addition to a panel-data approach the average regional endowment of these years is linked to the received funds in total. Due to a lack of explanation through regional development indicators, we considered local government performance, spatial dependencies and knowledge spillovers as determinants of the structural funds allocation.

Using a DEA approach we received independent technical efficiency measures of the local governments' public good provision. We employed these measures as indicators of the local government performance, respectively management facilities in dealing with structural programs. Furthermore we were convinced that the performance depends on the intrinsic knowledge of local actors. It is well known that the spatial diffusion of knowledge is one of the key factors explaining differences in economic growth, consequently we included the possibility of knowledge spillovers as well as of financial spillovers in our estimations. Due to spatial correlation in the funding distribution, i.e. that observations from nearby regions are more similar than would be expected on a random basis, spatial econometric approaches were applied to test for spatial correlation.

The estimations provide mixed results. The average income as well as the local government performance stand out as clearly positive and significant, supporting the assumption that the local government performance has a payments enhancing effect. There is a supporting character in the development plan formulation or co-financing management. The positive influence of the average income is in line, as the co-financing becomes more easily manageable. The significant influences of the regional endowment with agricultural used area is in accordance with the general

Table 6: Estimation results - spatial panel models: direct, indirect and total effects

Variable	Coeff (t-stat)	t-prob	Coeff (t-stat)	t-prob	Coeff (t-stat)	t-prob
	Pooled model with sptially lagged dependent variable, no fixed effects					
	direct effects		indirect effects		total effects	
Inc	0.389***	0	0.237*	0.087	0.625***	0
	(5.944)		(1.363)		(3.394)	
Spatm	-0.051	0.785	-0.019	0.529	-0.07	0.593
	(-0.789)		(-0.074)		(-0.237)	
Govperf	0.094*	0.067	0.432**	0.015	0.526***	0.006
	(1.502)		(2.196)		(2.544)	
	Pooled model with sptially lagged dependent variable, time period fixed effects					
	direct effects		indirect effects		total effects	
Inc	0.294***	0	0.266**	0.031	0.560***	0
	(4.108)		(1.871)		(3.848)	
Spatm	-0.068	0.878	0.041	0.42	-0.026	0.547
	(-1.169)		(0.203)		(-0.117)	
Govperf	0.078	0.116	0.377***	0.008	0.455***	0.002
	(1.196)		(2.429)		(2.857)	

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

purpose of SAPARD. The positive impact of the regional social capital endowment as well as of the mean age represent inner regional spillovers in information, finding of project partners and planning reliability. The generated quality of life measure is only significant in case of the average endowment approach. With respect to the structural program purpose to enhance the quality of life, the negative influence of quality of life is adequate. Already high quality of life regions receive less support. Regarding the test on spatial dependencies, the fundings a region received is influenced by the average raised funding of neighboring regions. The effect is more apparent in the panel-data approach. This seems comprehensible as the effects develop over the whole program duration.

Spillovers result form the government performance as well as from the average income. Knowledge gains from neighboring regions, and the exchange of information and experiences take place and lead to a more successful project participation. The differentiation in direct, indirect and total effects shows that the average income of an individual region causes a higher positive effect on the SAPARD funds of this region (included the feedback effects that arise from the changed income of the region on the SAPARD payments of all neighboring regions) than a gain in knowledge. In the panel data approach the total effect of the income also exceeds the impact of government performance. In case of government performance it is the inverse case. The indirect effect quadruples the direct effect in height. Therefore, a region profits most, if all neighboring regions achieve a gain in knowledge, i.e. not the knowledge of the own region is decisive but rather the cooperation with other well-performers.

In all, local government performance and income, inner-regional as well as of neighboring regions are decisive for the absorption of structural funds. The impact has to be seen in context to regional socio-economic circumstances. Further, spatial dependencies occur in the funds distribution that cannot be explained by variables given in the structural program layout; structural programs are formulated to achieve specific objectives. The requirements on a region to take part in a structural program are constituted as well. But a clear bias in fund distribution occurs when the distribution is only explained by the program subjects.

The following issues require further research: As regards the general objectives of structural policies to reduce intra- as well as international disparities the impact of structural funding on the quality of life level should be brought into focus. As structural programs are set out for a duration of six years, this study emphasizes the use of panel approaches to detect determinants of structural funding, especially with respect to spatial dependencies occurring in form of spatial spillovers. Beyond the estimated spatial Durbin models a Bayesian spatial Durbin model could be applied (Seya et al., 2010) to deal simultaneously with spatially lagged as well as not lagged explanatory variables. From a political advice perspective the co-financing principle commends an analysis in detail. The unexpected positive significant impact of the average income on the spent SAPARD funds seems to be in contrast to the general purpose of structural programs. Further, with regard to the importance of government performance the neighboring effects are astonishing. Therefore, convergence based on government performance and management facilities might be an important policy issue, as one region alone will be less successful than a region in cooperation with other regions.

Appendix

Table 7: Cross-correlation table

	Sap	Inc	Adm	Spatm	Govperf	Mage	QL	Agsec	Agarea
Sap	1								
Inc	0.4875	1							
Adm	-0.3548	-0.5786	1						
Spatm	0.1515	0.2739	0.2531	1					
Govperf	0.2052	-0.2346	0.058	-0.0504	1				
Mage	0.3543	0.3301	-0.0201	0.3078	-0.1978	1			
QL	0.4257	0.4707	-0.2977	0.4159	0.4395	0.1133	1		
Agsec	-0.3292	-0.5432	0.5962	0.0071	-0.0366	-0.0534	-0.4375	1	
Agarea	-0.098	-0.4617	0.3875	-0.1992	0.1957	-0.0075	-0.2845	0.5054	1

Figure 9: Estimation results: OLS-regression

Variable	**Coefficient**	**t-stat**	**z-prob**
Inc	0.396**	2.500	0.015
Adm	-0.137	-0.930	0.357
Spatm	-0.016	-0.120	0.903
Govperf	0.371***	2.840	0.006
Mage	0.286***	2.760	0.008
QL	0.036	0.220	0.825
Agsec	-0.424	-1.660	0.102
Aarea	0.472*	1.900	0.062
cons	-1.931**	-2.120	0.038
R^2		0.453	
Adj R^2		0.383	
$F_{(8,63)}$		6.509	

**** p < 0.01; ** p < 0.05; * p < 0.10*

Figure 10: SDM: Residual Plot with *(SDM_1)* and without *(SDM_0)* Govperf

Table 8: Estimation results: panel regression models (2002-2004)

	Random Effects GLS regression model			Random Effects tobit regression model		
Variable	Coeff	t-stat	z-prob	Coeff	t-stat	z-prob
Inc	0.464***	4.580	0.000	0.646***	4.380	0.000
Adm	0.009	0.100	0.924	-0.011	-0.090	0.929
Spatm	0.182*	1.700	0.089	0.177	1.340	0.179
Govperf	0.258***	3.050	0.002	0.340***	3.190	0.001
Mage	0.160**	2.140	0.033	0.181*	1.940	0.053
QL	-0.212*	-1.940	0.052	-0.314*	-2.250	0.024
Agsec	-0.400**	-2.260	0.024	-0.563**	-2.480	0.013
Agarea	0.377**	2.250	0.024	0.563***	2.630	0.008
cons	-2.079***	-3.240	0.001	-2.963***	-3.200	0.001
R-squared		0.376				
log-likelihood					-284.694	
$\chi^2_{(10)}$		90.71			64.36	
Prob > chi^2		0.000			0.000	
N		216			216	
Censored					56	
Uncensored					160	

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

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Table 9: Spatial Panel: Autocorrelation, error autocorrelation, time-period fixed effects

	Pooled model with spatially lagged dependent variable, no fixed effects			Pooled model with spatially lagged dependent variable, time period fixed effects			Pooled model with spatial error autocorrelation, no fixed effects			Pooled model with spatial error autocorrelation, time period fixed effects		
Variable	Coefficient	Asymptot	t-stat	Coefficient	Asymptot	t-stat	Coefficient	Asymptot	t-stat	Coefficient	Asymptot	t-stat
constant	-0.818	-1.565	0.118				-0.641	-1.016	0.310			
Inc	0.244***	2.747	0.006	0.090	0.917	0.359	0.269***	2.795	0.005	0.122	1.238	0.216
Adm	-0.020	-0.271	0.786	-0.110	-1.439	0.150	-0.038	-0.440	0.660	-0.118	-1.439	0.150
Spatm	0.179**	1.988	0.047	0.181**	2.060	0.039	0.179**	2.041	0.041	0.177**	2.045	0.041
Govperf	0.131*	1.810	0.070	0.113	1.568	0.117	0.121	1.497	0.134	0.119	1.565	0.118
Mage	0.088	1.402	0.161	0.112*	1.845	0.065	0.146*	1.850	0.064	0.133*	1.911	0.056
QL	-0.093	-0.993	0.321	-0.030	-0.320	0.749	-0.125	-1.357	0.175	-0.055	-0.599	0.549
Agsec	$-0.243^{\perp}$	-1.645	0.100	-0.181	-1.236	0.216	-0.250	-1.514	0.130	-0.186	-1.192	0.233
Agarea	0.235*	1.664	0.096	0.149	1.065	0.287	0.255	1.622	0.105	0.161	1.078	0.281
ρ	0.421***	5.698	0.000	0.276***	3.278	0.001						
teta							0.409***	5.271	0.000	0.244***	2.781	0.005
R-squared		0.415			0.443			0.387			0.430	
Rbar-squared		0.390			0.413			0.363			0.403	
$sigma^2$		0.660			0.629			0.692			0.643	
log-likelihood		-266.155			-258.223			-270.975			-260.170	

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$; $^{\perp}$ $p = 0.10$

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