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Research Article

FACTORS DETERMINING THE DEVELOPMENT OF MINIMUM COMPARABLE AREAS AND SPATIAL INTERACTION

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ABSTRACT

One popular strand of literature concerning economic growth and/or GDP focuses on the growth/GDP of minimum comparable areas (MCAs) but conducting research in this area is difficult due to data problems. To understand the nature of the micro-level structure, we estimate the determinants of the GDP of MCAs in Turkey since no single study covers all towns. We use spatial models and show that regional development policies should be based on the actual contiguity of MCAs, which is not currently considered in policies. We utilize Bayesian criteria to determine the best-fitting spatial weight matrix, whereas many previous studies have chosen such matrices subjectively.

Keywords: Minimum comparable areas; Towns; Regions; Growth; Spatial interaction.

JEL codes: R1, C21, O47

INTRODUCTION

Cities and minimum comparable areas (MCAs; towns, in this study) in a province have no official restrictions on the mobility of production factors. Labour and capital can freely move from one MCA to another. However, in many countries, certain MCAs grow continuously, whereas others suffer from poverty. It may be expected that the marginal returns of factors in different MCAs will be equal over time. However, there are some reasons that factors do not disperse efficiently among MCAs, as in the Feldstein-Horioka puzzle (Feldstein and Horioka 1980, Kisangani 2006, Ohta 2015 and several more), which was originally tested at state-level datasets. This issue should be taken seriously because it does not involve only a specific location. There are dynamic links from small units to cities, regions and even the country as a whole, and vice versa. As noted by Venables (2003), Overman (2011), Duranton and Puga (2013) and Hsieh and Moretti (2015), the contribution of cities' development to aggregate development should not be ignored[1].

Ignoring spatial interactions among MCAs may result in the application of inappropriate policies. Because MCAs are tied up in provinces and their policies and rules, the main research question may be the following: if MCAs are tied up in the "wrong" provinces or provincial administrative structures, does this affect their economic performance? We compared alternative interaction compositions of MCAs using rare datasets from Turkey. In this study, we attempt to determine the type(s) of interaction among MCAs (towns in this study) that can effectively affect their economic development estimating their GDP.

[1] Several previous studies have estimated small regional units' economic indicators. Some studies focus on MCAs and use spatial models. These studies include Resende (2013), Resende et al. (2015), Cravo and Resende (2015) for Brazil and Rupasingha and Goetz (2013) for the US. Deller et al. (2001) also used other models for the US. Other studies focus on *regional* growth/development using spatial models, such as Arbia et al. (2003) for Italy, Supińska (2013) for Central and Eastern European countries, Crespo-Cuaresma et al. (2009) and Sanso-Navarro and Vera-Cabello (2015) for the EU regions and Curran (2009) for the UK, Blash et al. (2020) for Russia, Huang et al (2020) for China Panzera and Postiglione (2021) for Europe. Other studies, however, focus on regional growth but do not use spatial models. These studies include Kallioras and Tsiapa (2015), Barro and Sala-i-Martin (1991), Hammond and Tosun (2011), Levernier et al. (2000), Dobkins and Ioannides (2001) and González-Val and Lanaspa (2016) for the US; Funke and Niebuhr (2005) for Germany; and Gennaioli et al. (2013) for regions of 110 countries,

In countries such as Turkey, there may be practical issues regarding the mobility of the factors among provinces or even towns: 1) Considerable disparities among local areas may arise from public policies such as incentives that are implemented at the provincial or regional level rather than at the town level. This structure may damage the interactions among towns. For example, even though two neighbouring towns are located in different provinces, they may engage in natural and complementary interactions. However, if their provincial policies do not consider interactions that may hinder economic activities, the economic development of the towns may be slower than expected. 2) The distribution of resources among towns along with the province equally, recklessly or politically rather than functionally may disrupt the improvement of towns.

Before the 2000s, Turkish provinces were powerful in terms of local administration. However, after Turkey’s entrance into the European Customs Union, the requisite data collection for monitoring economic development and public policies/expenditures (such as incentives) also began to rely on the Nomenclature of Territorial Units for Statistics (NUTS) in addition to those at the province level. Therefore, the structures and problems of towns have been ignored since, generally, the policies focused on regions or provinces. For example, although Denizli Province includes one of Turkey's richest cities, it also includes some of the country’s poorest towns (Dinçer et al. 1996 and 2003, Dinçer and Özarslan 2004). There are several examples in other provinces as well. Poor towns in developed provinces or regions do not benefit from public utilities effectively as much as poor ones located in poor provinces or regions do. Therefore, we posit there are alternate ways to form regional economic policies for administrative units, such as provinces, rather than applying the same policy to all towns. For example, incentives and regional economic policies for towns can be tabulated with different specifications and not applied by considering the feasibility and structural consistency. Given growth disparities and the importance of small units for global growth, it is interesting to estimate the economic development of small locations, such as towns, especially when countries are relatively large and possess diverse income, social structures and geographical characteristics. Turkey is a perfect example since it covers 783,562 square kilometres. Therefore, in this study, we estimate *the determinant of Turkish towns' GDP* during the 2008-2010 period[2].

The main contributions of this study are threefold. First, we test which type of interaction is more valid. In Turkey, provinces are strongly linked to central government policies. Similarly, all towns in the same province are subject to the same or very similar policies for incentives and other governmental issues. As noted above, if a town in a province is rich, this wealth may mask the poverty of other towns in the same province and result in inappropriate regional economic policies. Certain poor and disadvantaged towns are treated as rich because of the provincial income and may not benefit from positive discrimination. We hypothesize that if towns in the same province are subject to the same policies, they may not grow effectively. Instead, regional economic policies should rely on real-world interactions among contiguous areas. To test this issue, we rely on spatial models and test alternative policies and the actual policies are represented with a spatial weight matrix that assumes that all towns in a province are contiguous since they are subject to nearly the same policies and that governments implicitly accept that towns have positive interactions. However, the policies would be more effective if they considered interactions among contiguous areas. As a result, we test actual policies and alternative interactions and construct different weight matrices to test alternative policies. This structure may allow policymakers to assess alternative interaction simulations without incurring any costs.

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[2] Several studies have investigated the growth/GDP of provinces and regions in Turkey. Tansel and Gungor (1998) analysed productivity growth. Filiztekin (2000), Erk et al. (2000), Sagbas (2002), Gezici and Hewings (2004), Erlat (2005), Yılmaz and Kaya (2005), Bozkurt, S. (2009), Yildirim et al. (2009), Önder et al. (2010), Öcal and Yildirim (2010), Ersungur and Polat (2010), Yavan (2011), Aslan and Kula (2011), Zeren and Yilanci (2011), Karaalp and Erdal (2012), Ersoy (2013), Güçlü (2013), Akcagun et al. (2013), Akıncı and Yılmaz (2013), Taşkın (2014), Gerni et al. (2015), Özgül and Karadag (2015), Akçagün (2015), Değer and Recepoğlu (2016) analysed GDP growth. However, no work focuses on towns (MCAs in Turkey), except for descriptive studies and comparative studies.

Second, we employ spatial methods. Even though several previous studies have used spatial models, some of these studies did not use any criteria to choose the weight matrices and/or models, some of them choose weight matrices subjectively. Therefore, we use the Bayesian comparison approach to overcome this problem. In this study, we chose the best-fitting weight matrix and the best-fitting model combination using Bayesian selection criteria.

Third, we test some variables that have not typically been tested in previous studies. For example, the average slope and average (not just a specific point in the centre) altitude of towns is tested since geography may affect the economy.

Another important issue is that even though our datasets cover three years, we cannot estimate the panel model because we have time-invariant variables such as altitude and slope that did not produce reliable results over three years.

2. THEORETICAL STRUCTURE

In this section, we analyse and discuss the econometric and economic structures.

2.1 Economic structure

In the growth literature, Solow (1956), the Mankiw, Romer and Weil (MRW) (1992) and the Nonneman and Vanhoudt (1996) models are among the most used models. On the other hand, another strand of the literature considers regional growth and development models for smaller units. The models arise from a shared attraction to local culture, local employment centres, local natural resources, or other location-specific amenities in addition to growth models (Dawkins, 2003). These models are also based on conceptual foundations, exports, exogenous factors, political institutions or endogenous dynamics. Unfortunately, it is not easy to find all the fundamental variables when working with MCAs because of data limitations.

Following the relevant literature, we relied on the Nonneman and Vanhoudt model (1996), which is an extension of the Solow growth model. The model also covers location and natural factors as control variables. The closed functional form can be written as follows:

$$Y(i) = (L_R, L_C, K, G, C), \quad (1)$$

where L_R is raw labour, L_C is human capital, K is physical capital, G is geographic factors and C is climate factors.

2.2 Econometric structure

Spatial economics focuses on the interaction effects of the objects. If the data contain spatial dependencies, neglecting the appropriate model could lead to incorrect results and interpretations. In spatial economics, the structure of spatial dependence is implemented via the spatial weight matrix, which provides interactions between the spatial objects and has an effect on the estimated models.

Since the choice of the weight matrix represents the spatial interaction effects a priori, it will affect the estimation results of the spatial models. Therefore, determining an appropriate weight matrix among alternatives is essential. In this study, we used Bayesian posterior probability for a more objective selection method. In the approach, the information from data is used, and posterior probability for each weight matrix is calculated and the matrix with the highest posterior probability is selected.

In the literature, the spatial models are used with different spatial lags and tested against each other to reveal the most appropriate model. As a starting point, the general model includes all spatial lags such that the spatial lags of the dependent variable, independent variable and error term. If the spatial lag is only on the dependent variable, the model is called a spatial autoregressive model (SAR); if the spatial lags are in the disturbance term, the model is called a spatial error model (SEM); if the spatial lag is on the dependent and independent terms, the model is called a spatial Durbin model (SDM).

The general model can be written as follows:

$$Y = \alpha + \delta WY + X\beta + WX\theta + u, \tag{2}$$

$$u = \lambda Wu + \varepsilon, \qquad \varepsilon \sim N(0, \sigma^2 I).$$

The test results in our analysis indicate that the model that best fitted the data is the SDM. Therefore, we only describe the theoretical structure of the SDM to save space. Detailed information on the other models is provided in Elhorst (2013).

$$Y = \alpha + \rho WY + X\beta + WX\theta + \varepsilon, \tag{3}$$

where Y is an $N \times 1$ vector of dependent variables, X is an $N \times K$ vector of exogenous explanatory variables, α is a constant term, WY represents endogenous interaction effects, WX represents exogenous interaction effects, θ is $K \times 1$ unknown parameter, ρ is spatial autoregression, and W is a nonnegative $N \times N$ symmetric matrix. Therefore, the income of each MCA could be affected by the average of the independent variables in neighbouring MCAs' (WX) and neighbouring MCAs' income (WY) proxied by taxes. The SDM has three effects: direct effect, indirect effect and total effect. The diagonal elements of the matrix show the direct effect whereas the off-diagonals the indirect effect.

3. DATA

We analysed 819 Turkish towns for the period 2008-2010. The variable names and descriptive statistics are given in Table 1.

3.1 Dependent variable

We considered taxes as a proxy for the MCAs' (towns) GDP. We followed a procedure to ensure that this is suitable as a proxy: The official statistics in Turkey do not provide any data for towns. Therefore, we summed the towns' taxes and obtained taxes at the NUTS 3 level. Then, we estimated the correlation between taxes and the NUTS 3 level GDP. We found a 94% correlation between them, which provided support for the use of taxes as a proxy variable. However, taxes depend on registered income, which may lead to limitations. Additionally, the accumulation of taxes may cause some information loss. On the other hand, GDP figures are also measured from registered income and the losses from accumulation can be ignored. As result, taxes may be a good alternative if there are no GDP figures for towns. The data sets are obtained from the Ministry of Finance. In previous studies, several variables have been used to proxy GDP/growth. For example, Gerni et al. (2012) used taxes; Sutton et al. (2007), Henderson et al. (2009), Chen and Nordhaus (2011), Verma (2012), Zhou et al. (2015), Özpınar and Koyuncu (2016) used night-time light data; and Andrade et al. (2004) used sector datasets. It is clear that when estimating the growth of smaller units, using a proxy is usually a necessity. On the other hand, some towns are quite small and they cover smaller units that are distributed their lands therefore relying on night-time light data may not be effective use.

Figure 1 displays the three-year average provincial distribution of town income. The data label is on the left of the map. The poorest town is on the top, and the richest town is at the bottom of the label. It appears that a town that has a lower income makes the towns around it poorer (and vice versa) and that there are certain income clusters.

Figure 1. Distribution of town GDP calculated using ArcGIS

3.2 Independent variables

Several variables are considered to estimate the town's GDP based on the literature. The expected signs of explanatory variables are shown in the Table1 and explained as follows:

I. One of the most important differences in this study is the inclusion of *average* geographical variables, which have previously been neglected. The geographical variables[3], such as the average slope and average altitude, were calculated using electronic maps in the ArcGIS software. Slope and altitude are assumed to harm growth since a high slope and altitude may harm agriculture and urbanization.

II. Several previous studies focusing on the regional development level used the number of employees (Mankiw et al. 1992, LeVernieret al. 2000, Deller et al. 2001, Curran 2009, Cravo 2010, Hammond and Tosun 2011 and Akçagün 2015). The expected influence of an increase in labour is positive, and we use the number of employees, which was obtained from the Social Security Institution of Turkey (SGK).

III. In the literature, human capital in different forms is used extensively, depending on the theoretical model (Mankiw et al. 1992). Studies focusing on regional development also use human capital (LeVernieret al. 2000, Deller et al. 2001, Yılmaz and Kaya 2005, Sartoris and Igliori 2007, Bozkurt 2009, Curran 2009, Ocal and Yildirim 2010, Cravo 2010, Resende 2013, Gennaioli et al. 2013 Akçagün 2015, Cravo and Resende 2015 and Sanso-Navarro and Vera-Cabello 2015). Therefore, we used the literacy rate to proxy for human capital. We collected these data from the Turkish Statistical Institute (TURKSTAT/TUIK).

[3] Average values are used not only for specific points (such as downtown) but also for other points through towns. Average values may better measure the geographic situation.

Table 1. Descriptive Statistics

Variables	Expected sign	Mean	Standard Deviation
real GDP proxy		16.69	19.38
literacy rate	+	0.88	0.047
number of employees	+	9.51	11.78
slope	-	2.38	1.70
distance to the nearest city centre	-	3.85	3.55
length of highway/acreage	+	11.21	10.96
length of railway/acreage	+	9.15	9.93
average temperature (°C)	+	2.53	1.18
average humidity (%)	+	4.14	2.04
average altitude	-	6.62	6.28

IV. Similar to Deller et al. (2001), we used climate variables. It is expected that average temperature and average humidity – not extreme values – have a positive effect. These variables were obtained from the Turkish State Meteorological Service.

V. Another important variable group in the regional development literature is infrastructure and public spending (Deller et al. 2001, Sartoris and Igliori 2007, Curran 2009, Hammond and Tosun 2011, Akçagün 2015, Sanso-Navarro and Vera-Cabello 2015, Sanso-Navarro and Vera-Cabello 2015, Cravo and Resende 2015). To proxy for infrastructure and physical capital, we used highways and railways. The lengths of the highways and railways were computed using ArcGIS with electronic maps provided by the State Railways of the Republic of Turkey (TCDD). Roads and railways are assumed to have a positive influence on economic development since they represent transformational opportunities and public infrastructure.

VI. Each province has a central town, and nearly all important government offices are in these towns. These central towns are usually the largest in the provinces and have the greatest economic power. It is assumed that towns close to the central town will be positively affected due to their proximity to economic power. Some studies, such as Hammond and Tosun (2011), Gennaioli et al. (2013) and Sanso-Navarro and Vera-Cabello (2015), used proximity or being in a province centre to test this assumption. In the present study, we use the distance to the closest province centre to test the impact of distance on town growth. We compute the distance using electronic maps.

4. WEIGHT MATRICES, SPATIAL METHODOLOGY AND ESTIMATIONS

In this section, we used the MATLAB codes and routines developed by J. Paul Elhorst[4] and James P. LeSage[5].

4.1 Weight matrices

Selecting the weight matrix is the crucial step of spatial modelling because the weight matrix is inserted exogenously. We tested the following different weight matrices to determine the type of interaction that best fits the data.

- w_1 is a binary contiguity matrix in which all towns in a province are neighbours regardless of whether they are geographically adjacent.
- w_2 is a binary weight matrix of towns that are contiguous regardless of whether they are located within the same province.
- w_3 contains several alternative weight matrices that are built based on the different distances between towns (from 10 km to 200 km; increasing by 10 km each time, 20 alternative matrices).
- w_4 contains several alternative matrices that are built based on the closest neighbours to the 20 closest neighbours (adding the next closest town each time; this group includes 20 alternative matrices).

4.2 Variable selection

We checked the correlations among the variables apriori to ensure not to use the ones with high correlations. According to the correlation matrix, income, population, the number of undergraduate and graduate students, the number of employees and the number of

[4] (https://spatial-panels.com/software/).
[5] (https://www.spatial-econometrics.com/).

workplaces are highly correlated. Due to this structure and because we ignore population effects, we follow the procedures below.

The number of undergraduate and graduate students and the number of employees is divided by the population to use per capita figures. Additionally, the numbers of employees and workplaces have similar tendencies, and their correlation is nearly 1. Therefore, we dropped the number of workplaces from the estimations. Similarly, the number of undergraduates plus graduate students and the number of academics in universities have similar tendencies, and their correlation is nearly 1. Therefore, the number of academics was removed from the analysis. Finally, we did not use the number of undergraduate and graduate students per capita and the number of employees per capita in the same estimations because they are highly correlated. We used one of these latter variables in each alternative estimation. Although they were estimated separately, they produced very similar parametric results. However, we mainly relied on the number of employees per capita.

4.3 Test for spatial interactions and model selection

Regional data exhibits similarities by inhabiting the same space. However, many standard techniques assume that observations are independent and ignore the spatial dependence among errors. Thus, standard econometric techniques distort regression results and inferences when contiguity interactions are present. Spatial techniques have been widely applied to account for these problems.

In our analysis, we used the Bayesian posterior probabilities criteria to find the best weight matrix and the spatial model already explained. We start with the prior probabilities and then use the information in our data to get the posterior probabilities for the most likely spatial weight matrix and spatial model[6].

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[6] The most widely used spatial weight matrix is the contiguity matrix. The contiguity matrix is an $N \times N$ symmetric matrix of spatial units that share a comman border. Additionally, a spatial weight matrix can also be constructed for a distance

The literature describes different approaches that can be used to choose the correct weight matrix. Some researchers note that building a weight matrix is another important step besides spatial modelling (Paelink and Klaassen 1979 and Anselin 1988). Alternative methods can be used to achieve this outcome: comparing different weight matrices' parametric indicators (Ertur and Koch 2007), and determining a weight matrix by model diagnostic statistics (Stakhovych and Bijmoult 2009) or creating proxy variables that integrate spatial relations. However, these approaches will not prevent bias and inconsistencies that will occur when the incorrect weight matrix has been used (Mizruchi and Neuman 2008 and Farber et al. 2008). One effective solution to overcome these problems is to use Bayesian selection criteria as noted above that objectively select the matrix since their estimation is not affected by specification error (Lesage and Pace 2009). In light of the discussion, about spatial modelling and the weight matrix structure, we created four different groups of weight matrices for testing, as described above. We determined the weight matrix by relying on the Bayesian selection criteria proposed in Lesage (2014). We preferred to use a two-step approach for the representation. In the first step, we identified the best alternatives of w_3 and w_4 to be able to assess against the other two matrices, w_1 and w_2. In the third group (w_3) and the fourth group (w_4), we tested alternative matrices for towns within 10 km to 200 km of their neighbours, increasing 10 km each time, and alternative matrices for the closeness of the 1st to 20th towns by adding one neighbour each time, respectively. The combination of the best alternative weight matrices and model with the highest probability for w_3 and w_4 and each year are given in Table 2. All other alternatives are with the SDM model, and the other alternatives and their probability of them are not given to save space.

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or a k nearest neighbour. In a distance weight matrix, if the observations are within a specific distance, each element in the weight matrix will equal one; otherwise, the elements equal zero

Table 2. Simultaneous Bayesian comparison of the spatial weight matrices of the w_3 and w_4 groups

Data sets	w_3	w_4
Year 1	*7 neighbours*	*60 km*
	0.9631	*0.9631*
Year 2	*7 neighbours*	*70 km*
	0.9987	*0.9665*
Year 3	*7 neighbours*	*150 km*
	0.6395	*0.3290*
Average	*7 neighbours*	*70 km*
	0.9744	*0.9475*

The information in the cells at the intersection of rows and columns gives the best alternative contiguity structure regarding the combination of weight matrices and spatial models

Because the first and second alternative matrices are only one option, after determining the best alternatives for the third (w_3) and fourth (w_4) groups, we compared the matrices from all four alternative groups in each dataset, Year 1, Year 2, Year 3 and Average in the second

The matrix with the highest probability of the combination of four alternative matrices and three spatial models is the closeness matrix, which accepts the 7 closest neighbours in all datasets. This matrix is the best-fit weight matrix of all 50 alternatives of each dataset (Table 3). As a result, "w_3 and SDM" are the preferred combination of the weight matrix and the spatial model.

To estimate the model, we proxied the number of employees per capita for labour L_R, the literacy rate for human capital L_R and railway/acreage and highway/acreage for physical capital K. Regarding the control variables, we used the average slope, average altitude and distance to the city centre for geography and location G and average humidity and average temperature for climate C. The SDM's functional form, which is based on the OLS we estimated as the benchmark, is given as follows:

$$\begin{aligned}
\ln\left(\frac{GDP}{population}\right) &= \beta_0 + \beta_1 \ln\left(\frac{number\ of\ workers}{population}\right) + \beta_2\, literacy\ rate + \beta_3 \ln average\ slope + \\
&\beta_4 \ln distance\ to\ city\ center + \beta_5 \ln\left(\frac{highway}{acreage}\right) + \beta_6 \ln\left(\frac{railway}{acreage}\right) + \beta_7 \ln average\ temperature + \\
&\beta_8 \ln average\ humidity + \beta_9 \ln average\ altitude + \delta_1 W \ln\left(\frac{number\ of\ workers}{population}\right) + \delta_2 W\ literacy\ rate + \\
&\delta_3 W \ln average\ slope + \delta_4 W \ln distance\ to\ city\ center + \delta_5 W \ln\left(\frac{highway}{acreage}\right) + \delta_6 W \ln\left(\frac{railway}{acreage}\right) + \\
&\delta_7 W \ln average\ temperature + \delta_8 W \ln average\ humidity + \delta_9 W \ln average\ altitude + \delta W \ln\left(\frac{RGDP}{population}\right) + u. \quad (4)
\end{aligned}$$

4.4 Estimation results

Estimation results are given in Table 4. In the second, fourth, sixth and eighth columns of Table 4, we provide the estimation with OLS results of the average of the years, Year 1, Year 2 and Year 3, respectively. Next to each column, the SDM estimation results are also provided.

Table 3. Simultaneous Bayesian comparison of the spatial weight matrices of w_1, w_2, the best of w_3 and the best of w_4.

Weight matrices	Models	Year 1	Year 2	Year 3	Average
w_1	SAR	0.0000	0.0000	0.0000	0.0000
w_2	SAR	0.0000	0.0000	0.0000	0.0000
w_3	SAR	0.0000	0.0000	0.0000	0.0000
w_4	SAR	0.0000	0.0000	0.0000	0.0000
w_1	SEM	0.0000	0.0000	0.0000	0.0000
w_2	SEM	0.0000	0.0000	0.0000	0.0000
w_3	SEM	0.0000	0.0000	0.0000	0.0000
w_4	SEM	0.0000	0.0000	0.0000	0.0000
w_1	SDM	*0.2240*	0.0000	0.0000	0.0180
w_2	SDM	0.0000	0.0000	0.0000	0.0000
w_3	***SDM***	***0.7465***	***0.9987***	***0.9653***	***0.9891***
w_4	SDM	0.0295	0.0013	*0.0347*	0.0089

w1*: a binary contiguity matrix in which all towns in a province are neighbours regardless of whether they are geographically adjacent.*
w2*: a binary weight matrix of towns that are neighbours regardless of whether they are located within the same province.*
w3*: a weight matrix built using geographical coordinates: the closest neighbour matrices and includes the 7 closest towns. Depending on Table 3, the best alternatives for the third group weight matrices in each data set are the 7 closest neighbours.*
w4*: the best alternatives for the fourth group in Year 1, Year 2, and Year 3, and the averages are 60 km, 70 km, 150 km and 70 km, respectively.*
Notes: *The highest probability is shown in italics, and the sum of the probabilities in each column is 1.*

As the SDM model is the preferred model we will mainly discuss the result of this model. The direct effect of the lagged dependent variable is positive and significant in all alternatives, indicating that interactions are confirmed among neighbouring towns' GDP. This is important because urban spatial interactions unite neighbouring cities in urban agglomerations and city clusters, and the spatial interactions among the city (or town) clusters are among the main drivers of urban growth (Tan et al. 2016). Due to spatial interactions, the urban flow intensity increases, and the connections among the cities are enhanced. These invisible forces play important role in the regional development of urban agglomerations (Tan et al. 2016, Limtanakool et al. 2007). Because MCAs are small and need one another to develop, if policies are introduced based on real interaction relationships, scarce resources will be used more efficiently. One reason why some MCAs have not developed is that real interaction relationships are ignored and another reason is that both simple information and all appropriate policies that should be applied to the MCAs are ignored. Ineffective policies may cause incorrect infrastructure setups or non-functional incentives to industries that waste resources (Cheshire and Magrini 2009, Rey and Montouri 1999 and Niebuhr 2001). Therefore, the correct establishment of policies may improve regional development, and spatial interactions among city clusters should be considered in future regional planning (Venables et al. 2014, Tan et al. 2016). Because of this structure, determining the appropriate interaction type among MCAs is crucial.

Table 4. Regression results

	Average		Year 1		Year 2		Year 3	
Variables	**OLS**	**SDM**	**OLS**	**SDM**	**OLS**	**SDM**	**OLS**	**SDM**
β_0	-10.28 (7.30)	-10.55 (-4.35)	-9.95 (-6.45)	-9.92 (-3.70)	-9.40 (-6.67)	-9.71 (-4.02)	-12.06 (-7.95)	-13.74 (-5.24)
β_1 ln $(number\ of\ employees/population)$	0.13 (4.61)	0.11 (4.04)	0.14 (4.61)	0.13 (4.22)	0.12 (4.28)	0.11 (3.77)	0.14 (4.78)	0.11 (3.99)
β_2 $literacy\ rate$	0.87 (14.52)	0.52 (6.52)	0.79 (14.60	0.44 (5.68)	0.79 (13.52)	0.46 (6.14)	0.88 (11.75)	0.48 (5.57)
β_3 ln $average\ slope$	-0.29 (-6.33)	-0.43 (-6.04)	-029 (-5.72)	-0.40 (-5.14)	-0.28 (-6.25)	-0.45 (-6.35)	-0.29 (-6.07)	-0.40 (-5.49)
β_4 ln $distance\ to\ city\ center$	-0.17 (-7.98)	-0.22 (-10.26)	-0.18 (-7.82)	-0.24 (-10.20)	-0.17 (-7.99)	-0.22 (-10.15)	-0.14 (-6.48)	-0.21 (-9.24)
β_5 ln $(highway/acreage)$	0.07 (1.67)	0.08 (1.89)	0.04 (0.99)	0.06 (1.25)	0.08 (1.95)	0.09 (2.16)	0.08 (1.94)	0.09 (2.09)
β_6 ln $(railway/acreage)$	0.05 (3.09)	0.07 (3.82)	0.06 (3.67)	0.08 (3.82)	0.05 (2.79)	0.06 (3.52)	0.05 (2.64)	0.06 (3.40)
β_7 ln $average\ temperature$	0.58 (4.73)	0.59 (3.11)	0.73 (5.31)	0.57 (2.74)	0.58 (4.65)	0.62 (3.31)	0.59 (4.59)	0.53 (2.65)
β_8 ln $average\ humidity$	0.14 (5.05)	0.09 (2.57)	0.15 (4.78)	0.10 (2.38)	0.14 (4.92)	0.10 (2.66)	0.17 (5.74)	0.10 (2.73
β_9 ln $average\ altitude$	-0.06 (-2.59)	-0.07 (-2.73)	-0.06 (-2.18)	-0.08 (-2.57)	-0.07 (-2.79)	-0.08 (-2.92)	-0.05 (-2.07)	-0.06 (-2.34)
$\delta_1 W$ ln $(number\ of\ employees/population)$		0.19 (2.67)		0.08 (0.99)		0.22 (3.01)		0.17 (2.33)
$\delta_2 W$ $literacy\ rate$		0.41 (3.17)		0.35 (2.97)		0.39 (3.18)		0.50 (3.29)
$\delta_3 W$ ln $average\ slope$		0.29 (2.98)		0.26 (2.41)		0.34 (3.42)		0.28 (2.69)
$\delta_4 W$ ln $distance\ to\ city\ center$		0.25 (5.29)		0.27 (5.26)		0.24 (5.01)		0.27 (5.60)
$\delta_5 W$ ln $(highway/acreage)$		-0.10 (-1.06)		-0.10 (-0.96)		-0.11 (-1.15)		-0.08 (-0.78)
$\delta_6 W$ ln $(railway/acreage)$		-0.07 (-2.06)		-0.07 (-1.83)		-0.07 (-2.09)		-0.06 (-1.77)
$\delta_7 W$ ln $average\ temperature$		-0.04 (-0.17)		0.11 (0.37)		-0.08 (-0.31)		0.10 (0.35)
$\delta_8 W$ ln $average\ humidity$		0.01 (0.20)		0.02 (0.26)		0.00 (0.04)		0.04 (0.60)
$\delta_9 W$ ln $average\ altitude$		0.06 (1.25)		0.06 (1.17)		0.07 (1.43)		0.09 (1.82)
δW ln $(gdp/population)$		0.11 (1.79)		0.17 (2.68)		0.11 1.75)		0.20 (3.30)
R^2	0.51	0.54		0.53	0.49	0.54	0.45	0.50
Log-likelihood		-578.71		-667.12		-579.72		-613.05

The SDM columns have more information because of interaction parameters. t-values are in parentheses

According to the OLS and SDM results, the number of employees per capita, literacy rate, length of railways and highways, average temperature and average humidity are usually positive and significant. In contrast, the average slope, distance to the city centre and average altitude are negative and significant. To save space, we focus on the selected model and its results.

Interpreting the coefficients of the spatial models is important (Lesage and Dominguez 2012). A change in an independent variable will affect the dependent variable, influencing the counterpart variables with contiguous relations. Therefore, the direct and indirect effects are discussed below and are presented in Table 5.

The literacy rate, which is used to proxy human capital, is significant and positive for the direct effects, the indirect effects and the total effects. This result shows that improvements in human capital influence the focal town positively and those improvements in their neighbours' human capital positively influence the focal town. In any case, the spillover effect is positive.

The number of employees per capita is used to proxy raw labour, and its direct and indirect effects in all estimations are positive and significant, as expected. Because this variable contributes to the focal town's economy as input as well as consumers, the labour force in neighbouring towns supports the focal town. Additionally, the labour forces of towns may complete each other and may create a greater market for economic activity.

In the estimations, a town with a steep topography has a negative direct effect on the GDP level, whereas will increase with the indirect effect. This finding is reasonable since if the slope of the close towns is relatively high, it may positively affect the focal town's GDP level by providing advantages. According to the Ministry of Agriculture, 62.5% of the slopes of Turkish lands are higher than 15%, and lands with higher slopes may prevent the effective utilization of the water system and technology and may cause erosion. Additionally, steep topography may increase industries' investment costs to make steeply sloped land usable. When the residents of towns with steep topography seek to move to other towns where they can survive, they may logically consider moving to the closest nearby towns. Therefore, a disadvantage of one town may be an advantage to others. As a result, their total effects are negative, which is consistent with the direct effects. According to demographics in Turkey, towns with steep topography have lower population density, which may confirm the disadvantaged status of towns with steep topography.

Table 5. Direct and indirect effects

Variables	Data type	Direct Effects	Indirect Effects	Total Effects
$\ln(number\ of\ employees/population)$	Mean	0.11 (4.04)	0.22 (2.91)	0.34 (4.12)
	Year 1	0.13 (4.37)	0.11 (1.28)	0.24 (2.58)
	Year 2	0.11 (4.01)	0.25 (3.13)	0.36 (4.26)
	Year 3	0.12 (4.32)	0.23 (2.71)	0.35 (3.78)
$literacy\ rate$	Mean	0.53 (6.72)	0.51 (4.21)	1.04 (10.15)
	Year 1	0.45 (5.78)	0.50 (4.39)	0.95 (10.56)
	Year 2	0.47 (6.17)	0.49 (4.22)	0.96 (9.88)
	Year 3	0.50 (6.09)	0.72 (4.81)	1.22 (8.64)
$\ln average\ slope$	Mean	-0.42 (-5.99)	0.28 (2.68)	-0.14 (-2.05)
	Year 1	-0.39 (-5.17)	0.23 (2.01)	-0.17 (-2.03)
	Year 2	-0.44 (-6.46)	0.32 (3.21)	-0.12 (-1.87)
	Year 3	-0.40 (-5.77)	0.24 (0.22)	-0.16 (-1.98)
$\ln distance\ to\ city\ center$	Mean	-0.22 (-9.77)	0.25 (4.69)	0.03 (0.54)
	Year 1	-0.24 (-10.03)	0.28 (4.64)	0.04 (0.62)
	Year 2	-0.21 (-10.20)	0.24 (4.57)	0.03 (0.39)
	Year 3	-0.20 (-9.05)	0.28 (4.74)	0.08 (1.27)
$\ln(highway/acreage)$	Mean	0.07 (2.0)	-0.10 (-0.96)	-0.03 (-0.27)
	Year 1	0.05 (1.16)	-0.11 (-0.90)	-0.06 (-0.47)
	Year 2	0.09 (2.12)	-0.11 (-1.02)	-0.03 (-0.22)
	Year 3	0.08 (2.07)	-0.08 (-0.62)	0.01 (0.07)
$\ln(railway/acreage)$	Mean	0.07 (3.72)	-0.07 (-1.82)	-0.00 (-0.11)
	Year 1	0.08 (3.79)	-0.07 (-1.55)	0.01 (0.15)
	Year 2	0.06 (3.40)	-0.07 (-1.86)	-0.01 (-0.27)
	Year 3	0.06 (3.33)	-0.06 (-1.51)	-0.00 (-0.03)
$\ln average\ temperature$	Mean	0.59 (3.17)	0.03 (0.09)	0.62 (2.81)
	Year 1	0.59 (2.81)	0.24 (0.75)	0.82 (3.19)
	Year 2	0.63 (3.32)	-0.02 (-0.07)	0.61 (2.88)
	Year 3	0.52 (2.76)	0.25 (0.86)	0.78 (3.07)
$\ln average\ humidity$	Mean	0.09 (2.57)	0.02 (0.39)	0.12 (2.15)
	Year 1	0.10 (2.46)	0.04 (0.51)	0.14 (2.11)
	Year 2	0.10 (2.70)	0.02 (0.26)	0.11 (2.16)
	Year 3	0.10 (2.81)	0.07 (1.07)	0.18 (2.89)
$\ln average\ altitude$	Mean	-0.07 (-2.67)	0.06 (1.09)	-0.01 (-0.27)
	Year 1	-0.07 (-2.53)	0.06 (1.00)	-0.02 (-0.26)
	Year 2	-0.08 (-2.88)	0.07 (1.34)	-0.01 (-0.18)
	Year 3	-0.06 (-2.36)	0.10 (1.68)	0.03 (0.59)

t-values are in parenthesis

The direct effect of the distance to the city centre has negative effects. This finding may show the importance of being close to the central town. Our results support the results of Hammond and Tosun (2011), Gennailoli et al. (2013) and Sanso-Navarro and Vera-Cabello (2015). In contrast, the indirect effect of distance to the closest province centre is positive and significant, indicating that neighbouring towns are farther from provinces' centre towns and that the focal town is positively affected. In other words, when the focal town is closer to the centre town than to its neighbour, it has a greater advantage due to the positive effect of the central town.

The direct effect of highway length on acreage is positive and significant, whereas the indirect effect is negative and non-significant. Highways are one of the most important infrastructures, enhancing industry efficiency and providing access to markets and resources. Additionally, infrastructure such as highways may improve human capital by helping people connect with other people who live in the hinterland to take advantage of specialization and trade (Venables et al. 2014). Rupasingha et al. (2002) found that this variable has a positive effect on the GDP level. The indirect effects are not clear.

The direct effect of railway length is positive and significant, and this is not significant for the indirect effect. According to the Energy Productivity Group, a railway has a relatively long useful life, which may help to lower the cost of transportation and cargo, possibly promoting economic activity.

The direct effects of the average temperature and average humidity in a town are positive and significant, whereas the indirect effects are not significant. According to the literature, extreme climatic conditions hinder GDP levels (Bosetti et al. 2008, Brenner and Lee 2014). When we consider that the climatic conditions are relatively moderate throughout Turkey, the temperature and humidity may lead to improved industrial and agricultural production.

Only the direct effects of average altitude on growth are significant, and their signs are negative. Understandably, altitude may act as a hindering factor for the income level of towns. According to Sachs et al. (2001), the geographic structure is important for growth. Pereira (1973) reported that higher-elevation locations have disadvantages concerning transportation, communication and agricultural production. The indirect effects do not appear to be important for neighbouring towns.

The indirect effects results are usually consistent with the results of the interaction effects shown in Table 4.

5. CONCLUSION

In this study, we tested the hypotheses that interaction may contribute to rural development policies by promoting the inclusion of information on the contiguity of towns. There are important yet invisible interactions among units such as towns (and cities or regions). Ignoring the relationship among MCAs that interact involves not only ignoring essential information but also ignoring appropriate policies that should be applied to them. The first step in developing effective policies is evaluating which interactions are important. Therefore, in this study, we analysed whether and which types of interaction relations exist. The tests show that the models with a spatial dependency could not be rejected. Therefore, bias may arise when spatial models are not used. These results shed light on the actual economic interaction mechanisms and alternative structures/interaction mechanisms. We found evidence that the interaction within the 7 closest towns and regional policies should be developed simultaneously based on this structure, which will involve distributing the sources effectively instead of implementing policies that ignore this interaction and are based on a static provincial structure. The most critical issue is that the economic development of rural and remote places should not be based on regional averages. It would be useful to consider the structure and dynamics (such as incentives) of remote places.

Moreover, because our results confirm that spatial dependency is important, public investment should be strengthened to support interactions among towns. Infrastructure investment planning, in particular, should consider this structure. When examining the interactions among towns and their 7 closest neighbours, appropriate investment in highways and railways may help towns interact and grow.

According to the estimation results, human capital (literacy rate) is significant and positive for the direct, indirect and total effects on GDP. This again shows the importance of human capital. As one of the crucial factors, the number of employees per capita has a similar result, and as a proxy of capital, the direct effect of highway and railway length on acreage is positive and significant. Additionally, as Sachs et al. (2001) stressed that geographic structure is important regarding GDP, we also found some evidence of the importance of steep topography, which has negative direct and positive indirect effects on GDP. Towns take advantage of the steep topography of neighbours that are affected negatively. The direct effects of the average temperature and average humidity in a town are positive and significant, while the effect of average altitude on GDP is negative and significant, whereas the indirect effects are not significant. Finally, the direct effect of the distance to the closest province centre has negative effects and the indirect effect of distance to the closest province centre is positive and significant on GDP, showing the importance of being close to the central town that is similar to Hammond and Tosun (2011), Gennailoli et al. (2013) and Sanso-Navarro and Vera-Cabello (2015).

The main restriction in the study is the short period. It can be extended for long periods in future studies and a comparative study would be useful to investigate alternative income indicators to understand the nature of MCAs

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