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Determinants for Spatial Location of Pharmacies

Abstract

The topic of drug reimbursement is an important subject when one makes a decision on the construction of the reform of the health sector. Any change in the reimbursement list ends with a hot debate in the media and in everyday life. Incomprehensible pricing strategies used by pharmacies, force patients to seek those places that offer the necessary medication at the lowest possible price. Recognizing the economic opportunities for a profitable business, in recent years, a significant increase in the number of pharmacies is observed, and therefore, the number of these entities makes the process of selling drugs, especially those from the reimbursement list, almost impossible to control.

The article aims to reveal the spatial dependence for the pharmaceutical market on the example of pharmacies in poviat districts of Poland. An attempt is made to assess the prevalence of spatial dependence between the number of pharmacies and other determinants indicating health care resources, ageing process and the state of health of Poles. The summary of the study is to build a spatial model with its diagnosis for the number of pharmacies according to various socio-economic factors.

1. Introduction

In recent studies, both theoretical and empirical, the distinguishing between health economics and health care economics should be considered. As far as the health economics are concerned it is the scientific discipline that treats

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health as an economic issue. Following that definition, health economics relates to the process of manufacturing, exchange and consumption of health services. The issues of health economics continuously evolve under the influence of both internal and external surroundings of health care system and the health consideration of the population. On the other hand, the health care economics interests in the analyses of the health care functioning and the manner of financing of the health services in different organizational health care system types. Contemporary research in the field of health care economics, in major part, considers mostly the characteristics of the connection between the condition of national economy or/and the area of health care and health (in a broad meaning). Due to the diversity of the health care system problems the need for the interdisciplinary research and the use of appropriate research instruments induces.

The health economics is the science of allocating resources to the health system and within the system. In another words, health economics determines the subject of interest for economists working in this field, as well as, the methods of application of economic principles in health care.

In practice, several characteristic approaches to analysis can be used. One can highlight many important attributes of the economy, but in health economics three should be noted.

First of all, the scarcity of social resources. The classical economic analysis is based on the assumption that individuals must resign from a certain part of one resource in exchange for another. This means that on the national level, the growth in health expenditure to GDP results in reduction of other expenses. The opportunity cost (cost of giving up to get something else) of health care can be substantial. While most, pay attention to the monetary costs of goods and services, economists consider time as the most important scarce resource. Individuals sell time in exchange for remuneration, and most probably would refuse to work overtime, even if offered the rate of pay higher than normal, because it is not profitable. In a similar vein, many individuals resign from the use of admission free health care services because the costs of arrival at the health establishment and waiting for the service are too high.

Rational decision-making is another important attribute. Typically, economists examine economic problems of human behavior, assuming that the individual makes a rational decision. While rationality is defined as making the best possible choice to meeting the objectives of the limitations of resources, some of the individual’s behavior in the health care system may seem irrational. But when it comes to disputes about the rational behavior, economists often point out that the so-called irrational behavior often makes sense, but only if the achieved benefits are properly understood. The important characteristic of recent research in health care is the use of models in the analyses. In economics, models are developed to illustrate the ongoing or future possible processes, though should be understood as a reflection of reality. However, the models can be useful.

This article focuses mainly on the quantitative analyses of the health care system characteristics and attempts to apply the spatial statistics and spatial model in health economics.

2. Methods

The rapid development of the methodological principles and their application enabled the extensive use of the spatial econometrics methods and models in economic research in many other scientific fields, for instance: labor market economic growth, social interactions, environmental protection and health care.

In the economical spatial studies, the impact of exogenous variables on the endogenous variable must also include an interactive combination between the observations. This follows from the fact that space is not consisting of mutually insulated units. The spatial interaction between two objects may also affect other objects. It should be noted that according to the Tobler’s law, the closer the objects are geographically, the spatial interactions are more significant.

2.1. Testing the spatial dependence

The term of spatial autocorrelations refers to spatial clustering of similar values and their interdependence or interactions in reference to the geographical location of the objects. The study of interdependence relationships in geographic space requires the assumption on the existence of the functional relationship between the values of observed variables (Anselin 1988, p. 11). By definition, this means a lack of independence between the observations and the direct application of the Tobler’s law.

Spatial autocorrelation is a degree of correlation of the observed values of variable in a given location with the values of the same variable in another location. This means that the tested variable at the same time determine and is determined by its implementation in other locations. When testing for spatial dependence, two types of relations are considered: positive and negative autocorrelation. Confirming the positive autocorrelation, means in terms of location, the spatial accumulation: high or low values of observed variables. On the other hand, negative autocorrelation can be interpreted as the reverse of the positive autocorrelation - high values of observed variables adjoin to low and vice versa (Suchecki 2010, pp. 103-105).

There are several types of indicators for testing the spatial dependence. The most commonly used statistic is Moran's *I* (Cliff and Ord 1973), It is used to test the presence of global spatial autocorrelation according to the scheme described by standardized weights matrix **W**. Let us consider the variable *x* of observed values x_i in *n* different regions (i = 1, 2, ..., *n*). Then the value of the Moran's *I* statistics can be describe as follows (Suchecki 2010, p. 113).

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \tag{1}$$

where: n – number of observations, x_i, x_j – values of *x* variable in locations *i* and *j*, $\bar{x}$ – mean value of *x* variable, w_{ij} – elements of spatial weights matrix **W**.

While testing for spatial autocorrelation, a structure of hypothesis is examined, the null hypothesis for lack of spatial dependence against the alternative hypothesis for occurrence of spatial dependence. If the adjoined spatial objects are similar in reference to the descriptive characteristics, forming spatial clusters, then the value of Moran's *I* statistics is positive. If the adjoined spatial objects are varied (the spatial structure is regular, no clusters are formed) then the value of Moran's *I* statistics is negative. The Moran's *I* statistics ranges from (-1) to 1. For better visualizing of the type of Moran's *I* statistics, scatterplots are created and statistical significance graph is analyzed, the percentage of permutations for spatially random layout of variables is calculated. On this basis, it can be concluded about the existence or absence of spatial autocorrelation. The value of probability (*p*-value) is called the pseudo-significance level and is the ratio of the number of permutations for which $I_i > I_0$ to the number of all permutations made plus 1. The greater the *p*-value is, the less likely is the actual presence of autocorrelation.

Apart from the need to study global spatial autocorrelation, the literature indicates to obtain a detailed picture of the phenomenon of spatial dependence. Therefore, local indicators for spatial association analysis (Anselin 1995, pp. 93–115) (LISA) should be performed. It involves the study of correlation between the values of the variable in particular location in comparison to locations adjoined. Local Moran's I statistics I_i are calculated as follows (Suchecki 2010, p. 123):

$$I_i = \frac{\left(x_i - \bar{x}\right)}{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2}\sum_{j=1}^{n} w_{ij}\left(x_j - \bar{x}\right) \quad (2)$$

here: n – number of observations, x_i, x_j – values of x variable in locations i and j, $\bar{x}$ – mean value of x variable, w_{ij} – elements of spatial weights matrix **W**.

2.2. Spatial weights matrix W

In the construction of the measures of the spatial interactions, the spatial weights play a fundamental role. The spatial weights form the spatial weights matrix **W** and are calculated on the basis of distance or neighborhood matrices. The weight matrices can be constructed with the assumptions of different types and orders of contiguity (Suchecki 2010, pp. 33-34). The weight matrices are usually symmetric and in the analysis of spatial interaction, row standardization of the elements is assumed. This involves creating the transformed matrix, in which the sum of the elements in each row equals to 1. The values of the matrix elements are standardized with a closed interval <0,1>. For the construction of statistical measures, the standardization of the elements of the weights matrix is highly desirable, because of the possibilities of comparing different spatial processes and different models, therefor it is easier to interpret the processes of spatial autocorrelation and autoregression.

2.3. Spatial modeling

Spatial modeling improves the construction of the econometric model. If the analysis starts from the simple linear regression model, the application of cross-sectional sample as a localized data requires taking into account the spatial interactions that may occur between the studied units, which are expressed through the introduction of the model matrix of weights **W**. The interactions may relate to the endogenous variables – spatial autoregression is assumed, exogenous variables – cross spatial regression is assumed and random component – spatial autocorrelation of errors is assumed (Suchecki 2010,

p. 239). For the purpose of this article Spatial Autoregressive and Spatial Error Model are further described.

Spatial Autoregressive Model (or Spatial Lag Model) (Arbia 2006) assumes that the values of the endogenous variable in one location are dependent on spatially lagged mean values of the endogenous variable in adjoin locations. Formally, SLM model can be described as follows (Suchecki 2010, pp. 248-250):

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon},\ \boldsymbol{\varepsilon}:\mathrm{N}(\mathbf{0},\sigma^2\mathbf{I}) \tag{3}$$

where: **y** – endogenous variable, **X** – exogenous variables matrix, **β** – vector of structural parameters, **W** – spatial weights matrix, ρ – spatial autoregression parameter, **Wy** – spatially lag endogenous variable, **ε** – independent random component. In SLM models the significance of ρ parameter is tested.

Spatial Error Model can be tested, when in regression an autocorrelation in linear random component is assumed:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\xi},\quad \boldsymbol{\xi} = \lambda\mathbf{W}\boldsymbol{\xi} + \boldsymbol{\varepsilon},\quad \boldsymbol{\varepsilon} \sim \mathrm{N}(\mathbf{0},\sigma^2\mathbf{I}) \tag{4}$$

where: **y** – endogenous variable, **X** – exogenous variables matrix, **β** – vector of structural parameters, **W** – spatial weights matrix, λ – spatial autocorrelation parameter, **Wξ** – spatially lag error (mean error from adjoin locations), **ε** – independent random component. In SEM models the significance of λ parameter is verified. SEM model assumes the existence of spatial interactions (autocorrelation), caused by random factors (not included in modeling) or measurement errors (Suchecki 2010, p. 250).

3. Data set and research assumptions

3.1. Data source and specification

The source of data for the analysis is Local Data Bank of Central Statistical Office[1]. At the time of constructing the research the most current data was dated to 2010. The data used in the analysis was gathered on the NUTS 4[2]

[1] http://www.stat.gov.pl/bdlen/app/strona.html?p_name=indeks [day of access 14.07.2012].

[2] In accordance to the Nomenclature of Units for Territorial Statistics.

level – for 379 Polish poviats. As a subject of the research the number of pharmacies in Poland was accepted and a data set of potential explanatory variables was considered. The first group of explanatory variables was connected strictly with the health care and included:

- number of medical establishments,
- number of doctors, pharmacists.

The second group of explanatory variables included:

- gross monthly average income,
- number of people at age:
  - working,
  - pre-working,
  - post-working,
- number of people threatened with:
  - work environment,
  - work nuisance,
  - mechanical factors.

3.2. Main and specific objectives

The main objective of the article was to identify the spatial dependence on the example of the number of pharmacies in Polish districts. Apart from the main objective, some specific objectives were assumed as well. An attempt to verify the presence of spatial dependence between the number of pharmacies and explanatory variables[3] was made. As a summary of the research a spatial model for the number of pharmacies was designed and specified, depending on various factors.

3.3. Research hypotheses

For the purpose of the research hypotheses were formed. Firstly, if a patient goes to the doctor/medical establishment, then the pharmacy should be located close to that doctor/medical establishment. Secondly, people at post-

[3] Group consisting of data for: gross monthly average income, number of doctors, number of medical establishments, number of people at post-working age, number of people at risk because of the work environment.

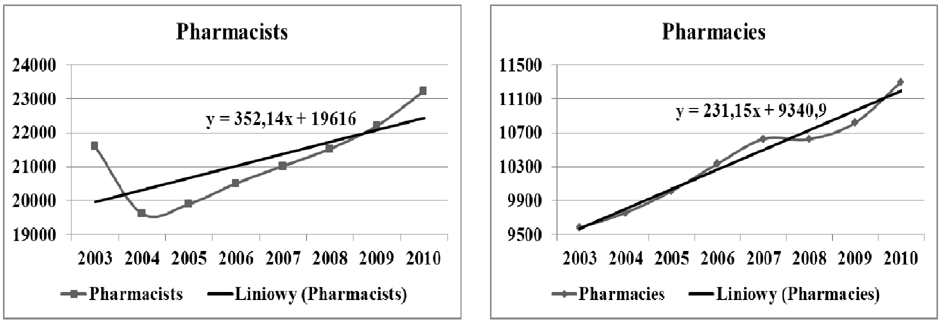
work age need an easy access to medicines. Thirdly, people who work and claim to be threatened because of their work environment need access to medicines.

4. Results

4.1. Baseline study

In the period 2003-2010, an increase in the number of pharmacies and their employees has been observed. The average growth rate noted for the number of pharmacies and the number of pharmacists amounted to 2.38% and 1.03%, respectively. The figure 1 below presents the tendencies observed in those time series and indicates that annually the number of pharmacies increased by 231,15 objects on average, and the number of pharmacists increased by 352,14 employees on average, ceteris paribus. Both parameters for the time variable *t* of the linear trend functions were significant.

Figure 1. Number of pharmacists and pharmacies



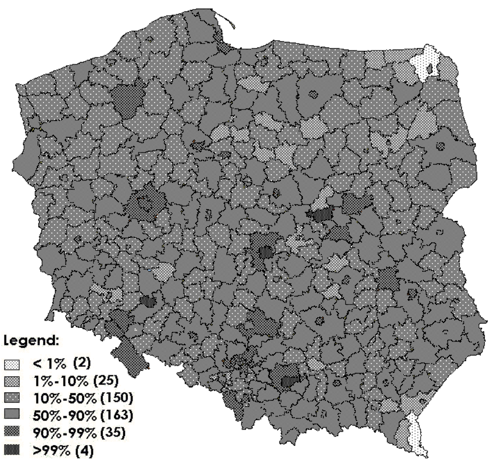
Source: developed by author, on the basis of CSO data in Microsoft Excel Software.

Comparing the ranks, a regularity is observed: on average, there are 2 pharmacists in a pharmacy, which is consistent with the guidelines of Ministry of Health.

4.2. Distribution of individual variables

Identifying a pattern for spatial autocorrelation is possible from the spatial distribution of analyzed variables. The figure 2 presents the geographical distribution of the number of pharmacies in Poland in 2010.

Figure 2. Spatial distribution of number of pharmacies variable – percentile map for 2010 data



Analyzing the distribution of number of pharmacies, areas of similar amounts of pharmacies can be identified. The brightest colors indicate that the lowest amounts of number of pharmacies can be observed in north-east and north-west Poland. In central and southern part of Poland, medium values were noticed. Outliers were possible to identify – dark and denser patterns specifies poviats of highest number of pharmacies.

Legend: dotted intensity indicates the scale of the phenomena – the higher values of the variable the darker and the denser pattern.

Source: developed by author, on the basis of CSO data in GeoDa 0.95.

4.3. Spatial autocorrelation

The spatial distribution map indicated that the location of pharmacies in Polish poviats was arranged in clusters of similar variable. To verify the hypothesis for spatial dependence, firstly, univariate Moran's *I* statistics were calculated and results are presented in table below.

Table 1. Univariate Moran's *I* for global spatial autocorrelation

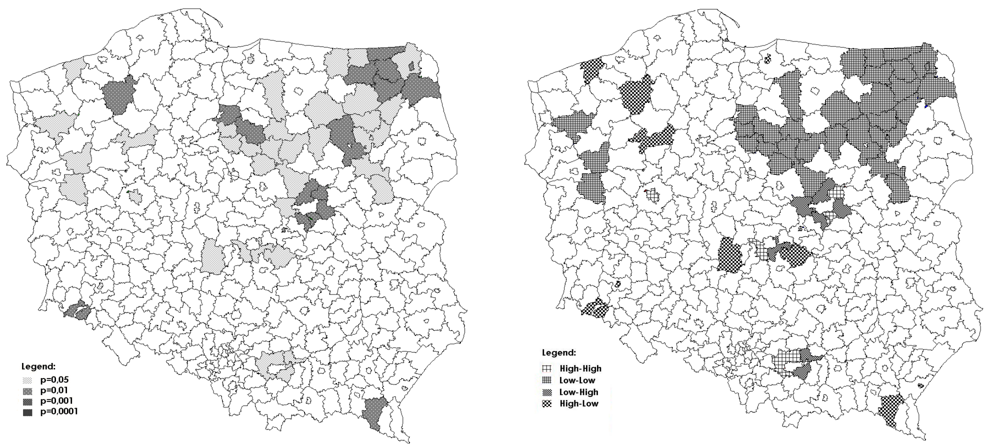
Variable	**Univariate Moran's I**	**p-value for α=0,05**	**Type of spatial autocorrelation**
number of pharmacies	0,0543	0,037	Positive
number of medical establishments	0,0465	0,084	None
number of doctors	-0,01	0,485	None
number of people at risk because of the work environment	0,207	0,001	Positive
number of people at post-working age	0,038	0,078	None
gross monthly average income	-0,037	0,152	None

Source: developed by author, on the basis of CSO data in GeoDa 0.95.

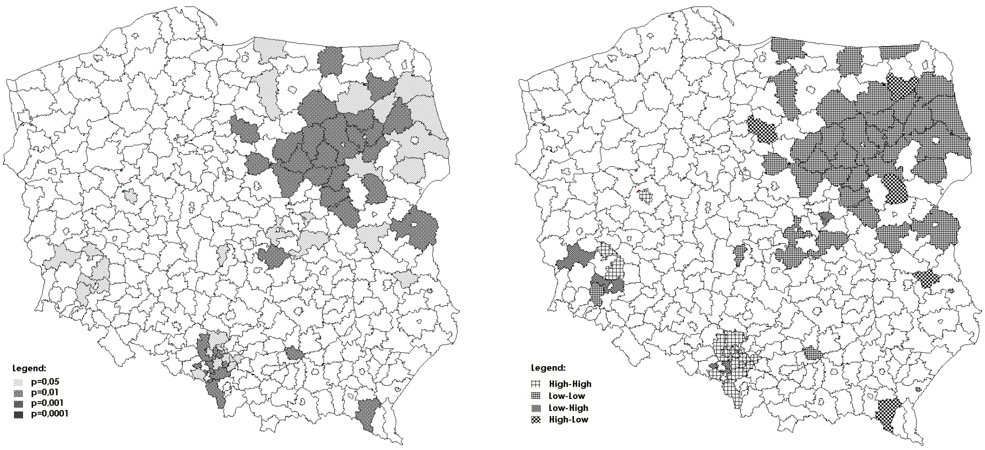
As the results show, only for the number of pharmacies and the number of people at risk due to the work environment the values of spatial autocorrelations were significant – assuming the 5% level of error, there were reasons for rejecting the null hypothesis in favor of the alternative. The results allowed to conclude that in both cases the correlations were positive, so there should be clustering of similar values of mentioned variables spatially observed. That led to further investigation and local indicators for spatial association *LISA* were calculated.

Figure 3. Local indicators for spatial association – significance and clusters maps

For number of pharmacies



For number of people at risk because of the work environment



Legend: maps on the left – significance maps – dotted intensity indicates areas of significant LISA statistics; maps on the right – clusters maps – checkered patterns indicate the neighboring areas of specific values of the variable.

Source: developed by author, on the basis of CSO data in GeoDa 0.95.

In both cases, it was possible to indicate the areas of specific values of the variables. The regions with a low number of pharmacies were pointed out in north-east Poland. The similar situation occurred for the number of people at risk due to the work environment. These results led to conclusion that between the endo- and exogenous variables a bivariate spatial dependence might occur. Following that bivariate Moran's *I* were calculated with reference to the number of pharmacies.

Table 2. Bivariate Moran's *I* for global spatial autocorrelation

Variable	Bivariate Moran's I	p-value for α=0,05	Type of spatial autocorrelation
number of medical establishments	0,04	0,25	None
number of doctors	0,00	1,00	None
number of people at risk because of the work environment	0,04	0,18	None
number of people at post-working age	0,04	0,11	None
gross monthly average income	-0,02	0,60	None

Source: developed by author, on the basis of CSO data in GeoDa 0.95.

As it turned out, none of the variables shown spatial autocorrelation of bivariate type with the endogenous variable – *p*-values for Moran's statistics indicated that there is no reason to reject the hypothesis of lack of spatial dependence.

4.4. Spatial modeling

Suggestion has been made that the methods of spatial econometrics can be used for researching geographic health care data. As a summary of the considerations of the possible determinants for the number of pharmacies, an initial model has been proposed, which was an attempt of a cross-spatial at time point analysis. The variables were selected on the basis of values of Pearson's correlation and the general model form was adopted as follows:

$$L_A = f(L_{ZOZ}, L_{LEK}, L_{ZSP}, L_{WPOP}, WB_{PM}, \varepsilon) \tag{5}$$

where:

Table 3. List of variables, their symbols and their impact on the endogenous variable

Symbol	Variable	Impact
L_A	number of pharmacies	N/A
L_{ZOZ}	number of medical establishments	+
L_{LEK}	number of doctors	+
L_{ZSR}	number of people at risk because of the work environment	+
L_{WPOP}	number of people at post-working age	+
WB_{PM}	gross monthly average income	+

Source: developed by author.

Having confirmed the existence of spatial dependence, it was advisable to assume the existence of the dependence in model construction. In this purpose the general model has been estimated with Ordinary Least Squares Method (OLS) and diagnosed for spatial dependence.

Table 4. Regression summary of output: Ordinary Least Squares estimation

Dependent Variable :	**LA**	Number of Observations:	379
Mean dependent var :	29.8074	Number of Variables :	5
S.D. dependent var :	42.8941	Degrees of Freedom :	374
R-squared :	0.970746	F-statistic :	3102.64
Adjusted R-squared :	0.970433	Prob(F-statistic) :	0
Sum squared residual:	20399.5	**Log likelihood :**	**-1293.07**
Sigma-square :	54.5442	**Akaike info criterion :**	**2596.15**
S.E. of regression :	7.3854	**Schwarz criterion :**	**2615.84**
Sigma-square ML :	53.8246		
S.E of regression ML: 7.33653			

Variable	**Coefficient**	**Std,Error**	**t-Statistic**	**Probability**
CONSTANT	1,885	0,690	2,730	0,007
LZOZ	0,202	0,023	8,611	0,000
LLEK	0,019	0,003	5,822	0,000
LZSP	0,002	0,000	3,886	0,000
LWPOP	0,001	0,000	12,997	0,000

REGRESSION DIAGNOSTICS

MULTICOLLINEARITY CONDITION NUMBER 12.41284

TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	1410.908	0.0000000

DIAGNOSTICS FOR HETEROSKEDASTICITY

TEST	DF	VALUE	PROB
Breusch-Pagan test	4	819.2369	0.0000000
Koenker-Bassett test	4	146.3062	0.0000000

SPECIFICATION ROBUST TEST

TEST	DF	VALUE	PROB
White	14	250.2937	0.0000000

DIAGNOSTICS FOR SPATIAL DEPENDENCE

TEST	**MI/DF**	**VALUE**	**PROB**
Moran's I (error)	**0.243092**	**7.2472706**	**0.0000000**
Lagrange Multiplier (lag)	**1**	**7.9233089**	**0.0048802**
Robust LM (lag)	**1**	**0.7817883**	**0.3765948**
Lagrange Multiplier (error)	**1**	**50.0300481**	**0.0000000**
Robust LM (error)	**1**	**42.8885274**	**0.0000000**

Source: developed by author, on the basis of CSO data in GeoDa 0.95.

After the first estimation, the coefficients of explanatory variables turned out to be significant – assuming the 5% level of error. The impact of each exogenous variable was consistent with previously made assumptions. As the results showed, the proposed model defined the complete changeability of endogenous variable in 97% and the standard error of regression indicated the +/- 7,38 miscalculation. What's more, the multicollinearity condition test did not indicate for the linearity problem, but unfortunately, the assumption for normality of errors was not fulfilled. Test for heteroskedasticity indicated problem of heterogeneity of variance. There is a possibility that the assumptions for normality of errors and homogeneity of variance could be granted by modifying the general model with spatial component.

As the diagnostics for spatial dependence module showed, introducing the spatial effects[4] to the model indicate the existence of spatial dependence. The Moran's *I* statistics was highly significant. This confirmed the necessity to use a model with spatial component. Looking at the values of Robust Lagrange Multiplier probability, it was highly recommended to select a Spatial Error Model (the Spatial Lag Model was insignificant). SEM model was constructed and estimated with Maximum Likelihood estimation (table 5).

[4] Spatial weights matrix **W** was used – row-standardized, first order, queen contiguity matrix.

Table 5. SEM summary of output: Spatial Error Model - Maximum Likelihood Estimation

Dependent Variable	: **LA**	Number of Observations	: 379
Mean dependent var	: 29.807388	Number of Variables	: 5
S.D. dependent var	: 42.894081	Degree of Freedom	: 374
Lag coeff. (Lambda)	: 0.443498		
R-squared	: 0.975087	R-squared (BUSE)	: -
Sq. Correlation	: -	**Log likelihood**	**:-1270.366036**
Sigma-square	: 45.836938	**Akaike info criterion**	**: 2550.73**
S.E of regression	: 6.7703	**Schwarz criterion**	**: 2570.419753**

Variable	**Coefficient**	**Std.Error**	**z-value**	**Probability**
CONSTANT	2,966	0,804	3,687	0,000
LZOZ	0,200	0,022	8,886	0,000
LLEK	0,023	0,003	7,900	0,000
LZSP	0,002	0,000	4,860	0,000
LWPOP	0,001	0,000	12,916	0,000
LAMBDA	**0,443**	**0,061**	**7,219**	**0,000**

REGRESSION DIAGNOSTICS

DIAGNOSTICS FOR HETEROSKEDASTICITY

TEST	**DF**	**VALUE**	**PROB**
Breusch-Pagan test	4	13020.8	0.0000000

DIAGNOSTICS FOR SPATIAL DEPENDENCE

TEST	**DF**	**VALUE**	**PROB**
Likelihood Ratio Test	**1**	**45.41532**	**0.0000000**

Source: developed by author, on the basis of CSO data in GeoDa 0.95.

After the final estimation, the coefficients of the explanatory variables turned out to be significant, assuming the 5% level of error. The impact of each exogenous variable was consistent with previously made assumptions. The most important fact was the significance of λ parameter, which confirmed the existence of spatial dependence and indicated the influence of random factors or measurement errors on the number of pharmacies in Poland. Diagnosis for spatial dependence (Likelihood Ratio test) was significant, which indicated that application of SEM model for explaining the changes in the number of pharmacies in Poland in 2010 eliminated the problem of spatial autocorrelation in data, but did not deal with the problem of heterogeneity.

5. Discussion and Conclusions

The implementation of spatial interactions improved the fit of model:

Table 6. Criterions of fit for OLS and EM

Criteria[5]	**OLS**		**SEM**
Log likelihood	-1293,07	<	**-1270,37**
Akaike	2596,15	>	**2550,73**
Schwarz	2615,84	>	**2570,42**

Source: developed by author, on the basis of CSO data in GeoDa 0.95.

All of the criteria received for SEM model indicated the better usage of that model, comparing with the OLS. Unfortunately, due to the high heterogeneity of Polish poviats it was not possible to deal with the problem of heteroskedasticity. The model adjusted for spatial dependence (SEM) – eliminated the problem of spatial dependence in the data.

Apart from the strictly technical results and findings of the analyses, it should be emphasized that the methods of spatial econometrics can be widely used in health care analyses, for instance, in developing a tool/model for defining the determinants for the number of pharmacies in Poland. It was confirmed, that on average when five new medical establishments are found in a poviat, then a pharmacy appears in that region, as well. The methods for revealing the spatial dependence allowed to identify the areas of occurrence of spatial autocorrelation for the number of pharmacies and the number of people at

[5] It is not possible to compare the R^2 of OLS and SEM models, instead values of Log likelihood, Akaike and Schwarz criterions are used. Better model has higher values of Log likelihood, lower values of Akaike and Schwarz criterions.

risk due to the work environment. Moreover, the research confirmed the need to incorporate spatial interaction factor in the modeling of health care on the example of the number of pharmacies.

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Streszczenie

DETERMINANTY LOKALIZACJI PRZESTRZENNEJ APTEK

Tematyka refundacji leków to istotne zagadnienie przy podejmowaniu wszelkich decyzji dotyczących kształtu reform dla sektora opieki zdrowotnej. Każdorazowa zmiana wykazu leków refundowanych kończy się gorącą debatą w mediach i w codziennym życiu. Niezrozumiałe strategie cenowe, stosowane przez apteki, zmuszają pacjentów do poszukiwania tych miejsc, które oferują niezbędny lek w jak najniższej cenie. Dostrzegając możliwości dobrego biznesu ekonomicznego, na przestrzeni ostatnich lat, obserwuje się znaczący wzrost liczby aptek, a w związku z tym, liczebność tych podmiotów uniemożliwia pełną kontrolę w procesach sprzedaży leków, zwłaszcza tych z list refundowanych.

Celem artykułu jest wykazanie przestrzennych zależności obserwowanych na rynku farmaceutycznym na przykładzie liczby aptek w powiatach Polski. Podjęta została próba oceny występowania przestrzennych zależności pomiędzy liczebnością aptek a liczbą lekarzy, liczbą zakładów opieki zdrowotnej, jak również innych determinant wskazujących na proces starzenia się społeczeństwa i stanu zdrowia Polaków. Podsumowaniem badań jest próba budowy modelu przestrzennego i jego diagnoza dla liczby aptek w zależności od różnych czynników społeczno-gospodarczych.