ARGUMENTA OECONOMICA
No 2 (43) 2019
PL ISSN 1233-5835

Grażyna Trzpiot, Agnieszka Orwat-Acedańska**

THE CLASSIFICATION OF SPATIAL QUANTILE REGRESSION MODELS FOR HEALTHY LIFE YEARS IN EUROPEAN COUNTRIES

EU countries are heterogeneous in terms of healthy life years (HLY). A quantile spatial autoregression model is employed to identify the factors affecting HLY. Quantile regression allows to measure the impact of covariates on different parts of the conditional distribution of a dependent variable. This is especially useful if the distribution is asymmetric or trimmed. Quantile spatial autoregression models add the spatial dimension to the standard quantile regressions. The aims of the study are as follows: identification of the factors affecting healthy life years of men and women in the EU countries, and clustering of the estimates obtained for the different quantile orders. We analyze to what extent spatial quantile regression can be useful in studying the behavior of HLY. We use exogenous factors belonging to three groups: socio-economic, healthcare and lifestyle. After initial estimation of the models for 19 quantile orders, the insignificant factors are removed and the remaining parameters are re-estimated. The final estimates are then clustered to facilitate the interpretation of the results. Instrumental variables method coupled with bootstrap techniques are employed for estimation and inference while the k-means algorithm is used for clustering. We find that the impact of the factors on HLY varies for different quantile orders. In general, the quantiles of low and medium orders are affected by the factors from all the three groups (socio-economic, healthcare and lifestyle). For the medium and high orders, the socio-economic factors are no longer important. We argue that the spatial quantile autoregression models offer a new perspective for studying the factors affecting HLY in the EU countries.

Keywords: healthy life years, multivariate spatial quantile autoregression, quantile regression
JEL Classifications: C31, I14
DOI: 10.15611/aoe.2019.2.05

1. INTRODUCTION

Life expectation is a measure that used to be utilized as one of the indicators for quality of life in a population. However, it has been argued recently that it should be replaced by healthy life years (HLY) because longer life does not need not be associated with a healthier one (Robine, 2006). Generally, HLY is defined as the expected remaining healthy life

* Department of Demography and Economic Statistics, University of Economics in Katowice.

years without a disability. This measure is a good proxy for the general level of health in a population which affects the productivity of labor, labor supply, human capital as well as public spending, among others. Investment in health is one of the priorities of the "Europe 2020" strategy, which aims at promoting a sustainable development in Europe. Implementation of the strategy as well as public health management require in-depth studies on factors affecting healthy life years in Europe. In 2015, the lowest value of HLY was observed in Lithuania – 54.1 years for women and 51.8 years for men. On the other hand, Malta is characterized by the highest HLY for women (74.6 years) whereas Sweden (74 years) and Malta (72.6 years) dominate for men. One can also notice a considerable differentiation in HLY between the EU countries. The differences between the highest and the lowest values exceed 20 years for women and 22 years for men.[1]

The high differentiation in HLY exemplifies the severe disparity in quality of life among European countries. The identification of factors determining these differences requires dependency measures that account not only for spatial effects but also for the considerable differences in the probability distribution of the analyzed variable. The impact of the potential important factors can vary among the considered countries. The classical statistical procedures that are based on simple averages describing expected values only (like models based on standard regression) can lead to a misleading inference on the factors affecting HLY. We extend the *spatial autoregression* models (SAR) using *quantile spatial autoregression regression* models (QSAR). The quantile estimation of the spatial model sheds more light on the spatial dependencies in different parts of the average life length distribution. The multiple quantile spatial autoregression models are used in order to account for substantial differences in the healthy life years and life quality between the EU members. Quantile regression allows for studying the dependencies between variables in different quantiles of the response distribution.

The main hypothesis of this work is that the quantile spatial autoregression method is a useful tool for identifying the factors affecting HLY of men and women in European countries. It stems from the following research questions:

– Which factors affect the healthy life years of the inhabitants of European countries in different parts of the conditional distribution of HLY?
– Is spatial quantile autoregression a useful approach in determining the factors affecting the healthy life years of men and women in European

[1] Own calculations based on EUROSTAT data for 2015.

countries (does it make sense to study the relationship between healthy life years and some factors separately for different parts of the HLY distribution)?
- Is it possible to meaningfully cluster the coefficients obtained from quantile regressions for different quantiles?
- Is it possible to point out representative estimates for each cluster summarizing the investigated relationship for each part of the conditional HLY distribution?

The main aim of the paper is the implementation of quantile spatial autoregression models for healthy life years in European Union countries. The goal is pursued by an analysis of the factors affecting healthy life years of men and women in these countries. The second aim is clustering the estimates obtained from the studied models.

This work builds on and extends the research carried out by (Orwat-Acedańska and Trzpiot, 2016b). After performing the model selection procedure that consists of specification, estimation and inference, the final estimates for different quantiles are clustered thus considerably facilitating the interpretation of the results. Parameters of the models are estimated using the instrumental variable Kim and Muller method (Kim and Muller, 2004). Confidence intervals and p-values are bootstrapped. The K-means procedure is employed for clustering the estimates.

The paper is organized as follows. First, we introduce the essence of HLY measurement and literature review. The third section introduces research methodology. In the first subsection of this section we describe the SAR model. The next subsection introduces the concept of the quantile regression. Then, we blend the two methodologies and introduce the QSAR model. Section 4 contains the empirical analysis; it consists of two subsections. First, we describe the explanatory variables used in the study and the main assumptions used in the empirical study. Then we present and discuss the results, and the final section concludes the paper.

2. HEALTHY LIFE YEARS – THE ESSENCE OF MEASUREMENT AND LITERATURE REVIEW

The Healthy Life Years indicator (HLY) is one of the European Structural Indicators monitored by Eurostat and also called *Disability-Free Life Expectancy* (*DFLE*) (Gromulska et al., 2008). It is also known as a measure of health expectancy (Robine et al., 2000). This is based on limitations in daily activities and therefore measures the number of remaining years that a person of a particular age can expect to live without disability. **Health expectancies** were first developed to address whether or not longer life is being accompanied by an increase in the time lived in good or in bad health. Therefore, health expectancies divide life expectancy into life spent in different states of health. In this way they add the dimension of quality to the quantity of life lived. The measure blends data on mortality (age at death) with susceptibility to disease (the age specific proportion of population with and without disabilities). Good health is defined by the lack of limitations resulting from disability. The most common method used to calculate health expectancies is the Sullivan method which was developed in 1971. HLY is calculated as follows (Sullivan, 1971):

$$HLY_s = \frac{\sum_{i=s}^{\omega} YWD_i}{l_s}, \tag{1}$$

$$YWD_s = L_s\left(1 - prev_s\right), \tag{2}$$

where: YWD_s – the number of years of life without disability at the age of s, l_s – number of s-year-old people surviving to s completed years, L_s – total number of life years at age s based on life expectancy tables, $prev_s$ – frequency of disabilities occurrences. The method is based on two main parts: a life table and the observed prevalence of the population in healthy or unhealthy conditions. The life table enables to calculate the life expectancy for each age s (or age category s in the case of an abridged life table).

The values of HLY have been compiled and published since 2004 for the EU member states (Wróblewska, 2008). These data were subsequently used in many studies, for example: Doblhammer and Kytir (1998), Charafeddine et al. (2011), Van Oyen et al. (2008), Vrabcová et al. (2017), Brønnum-Hansen (2017), Cambois et al. (2013), Frova et al. (2010), Dubkova and Krumins (2012), Petrauskiène et al. (2010), Majer et al. (2013), Gromulska et al. (2008), Bengtsson and Scott (2011), Gutiérrez-Fisac et al. (2010), Olatunde et al. (2010).

Health expectancy measures can be used to compare different subpopulations defined for example by sex, occupation, or social factors as well as to make intercountry comparisons (Robine et al., 2003). The following studies focus on the health expectancy measures in single and in groups of EU countries: Jagger et al. (2008), Jagger (2006), Perenboom et al. (2003), Robine and Jagger (2003), *Cambois and Robine* (2013), Fouweather et al. (2015).

This paper aims at identifying the socio-economic factors that are related to health expectancy in the European countries. As far as we know, this issue has not been studied previously. Furthermore, we argue that one has to go beyond the standard statistical and econometric procedures based on the conditional mean analysis. Instead, we propose applying quantile regression that allows to identify the differences in the studied relationships for different parts of the dependent variable conditional distribution. In our opinion, this is also an important contribution to the literature. Quantification of the factors affecting population health should help in preparing reliable programs of national and international public health management strategies.

3. RESEARCH METHODOLOGY

3.1. Spatial Autoregressive Model – SAR model[2]

The SAR[3] model has the following form (Anselin, 1988; Suchecki, 2010):

$$\mathbf{Y} = \rho\mathbf{WY} + \mathbf{X\beta} + \boldsymbol{\varepsilon}, \tag{3}$$

where: $\mathbf{Y}$ – vector of dependent variable realizations, $\mathbf{W}$ – spatial weight matrix, ρ – autoregression parameter, $\mathbf{X}$ – matrix of covariates realizations, $\boldsymbol{\beta}$ – vector of parameters, $\boldsymbol{\varepsilon}$ – error terms vector. Model (3) is a linear regression model with the additional spatial autoregression term. Spatial autocorrelation measures the correlation between the observed value of a variable in one localization and its value in another localization (region, for example). Spatial autoregression is represented by the spatial lag term $\rho\mathbf{WY}$ of the dependent variable. The vector of the error terms has a multivariate normal distribution:[4]

$$\boldsymbol{\varepsilon} \sim N(\mathbf{0}, \sigma\mathbf{I}). \tag{4}$$

The least squares estimator of the parameters of model (3) is inconsistent (Lee, 2002). Therefore, many consistent alternatives have been proposed, particularly maximum likelihood, instrumental variables (Anselin, 1988), generalized method of moments or two-stage least squares (Lee, 2007). For

[2] Section 3 is taken from Trzpiot and Orwat-Acedańska (2016).
[3] In the literature, some names of the model are utilized interchangeably. Using the SAR term, we follow LeSage and Pace (2009).
[4] In the paper we do not consider the model with correlated error terms. The quantile versions of such a model can be estimated using Bayesian methods only.

large-scale spatial models, Bayesian estimation is also employed by LeSage (1997) as well as Lum and Gelfand (2012).

In the case of the error term with asymmetric distribution, fat tails or heteroscedasticity as well as outliers, the standard estimation and inference techniques have low power. This comes as a consequence of large estimation errors of the parameters or the error term variance. More importantly, the standard SAR methodology, as a conditional expected value model, focuses solely on the relationships observed in the central part of the outcome distribution. Therefore, it cannot provide any insights into dependencies in the other parts of the distribution. This is not the case for quantile regression which allows studying the impact of covariates on the outcome in any point of the outcome distribution.

3.2. Quantile Regression Model – QR

We analyze the problem of the estimation of a vector of parameters $\boldsymbol{\beta}$ for a sequence of random variables $Y_1, Y_2, \ldots, Y_n$ taken with distribution $P(Y_i < y) = \Im\left(y - \mathbf{X}_i^{'}\boldsymbol{\beta}\right)$, where $\mathbf{X}_i = \left(X_{i1}, X_{i2}, \ldots, X_{ik}\right)^{'}$ is a column of $n \times k$ covariate matrix $\mathbf{X} = \left(\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_n\right)^{'}$, $i = 1, 2, \ldots, n$ and the distribution F is unknown. The point of departure for quantile regression is the conditional quantile function of a random variable Y:

$$Q_{(\tau)}(\mathbf{Y} \mid \mathbf{X}) = F^{-1}(\tau \mid \mathbf{X}), \tag{5}$$

where $\tau \in [0,1]$ denotes the order of a quantile. The quantile regression model of order τ takes the following form:

$$Y_i = \mathbf{X}_i{}'\boldsymbol{\beta}^{(\tau)} + \varepsilon_i^{(\tau)}, \tag{6}$$

where $Y_i \equiv Q_{(\tau)}(Y_i \mid \mathbf{X}_i)$, $\boldsymbol{\beta}^{(\tau)} = \left(\beta_1^{(\tau)}, \beta_2^{(\tau)}, \ldots, \beta_k^{(\tau)}\right)^{'}$ is the vector of the sensitivity coefficients of the conditional quantile on the changes in values of covariates, and $Q_{(\tau)}(\varepsilon_i^{(\tau)} \mid \mathbf{x}_i) = 0$. A distribution of independent random variables $\varepsilon_i^{(\tau)}$ is left unspecified, which is one of the virtues of the method as far as robustness to outliers is concerned. If $\boldsymbol{\beta}(\tau)$ is independent from τ, then the quantile model collapses to a model $E(Y_i \mid \mathbf{X}_i) = \mathbf{X}_i^{'}\boldsymbol{\beta}$ with a constant variance of an error term, otherwise, the model implies the variance that a quantile of distribution of Y_i depends on $\mathbf{X}_i$.

The model's estimation stage[5] is performed for a given quantile τ. Assuming that observations y_i, $i = 1,2,\ldots,n$ are treated as a random sample of the regression process $u_i = y_i - \mathbf{x}_i^{'}\boldsymbol{\beta}$ with unknown distribution $\Im$, Koenker and Basset (1978) defined a τ-th quantile regression estimator $\mathbf{b}^{(\tau)} = \left(b_1^{(\tau)}, b_2^{(\tau)}, \ldots, b_k^{(\tau)}\right)^{'}$, which solves the following problem:

$$\min_{\mathbf{b}\in\Re^k}\left[\sum_{i\in\{i:\, y_i \geq \mathbf{x}_i^{'}\mathbf{b}\}} \tau\left|y_i - \mathbf{x}_i^{'}\mathbf{b}^{(\tau)}\right| + \sum_{i\in\{i:\, y_i < \mathbf{x}_i^{'}\mathbf{b}\}} (1-\tau)\left|y_i - \mathbf{x}_i^{'}\mathbf{b}^{(\tau)}\right|\right] \tag{7}$$

Problem (7) has always a solution and for continuous distributions, it is unique. Since problem (7) can be transformed to a linear optimization problem, its solution can be found using the internal point method (Portnoy and Koenker, 1997). The approach is regarded as a non-classical method due to its robustness. Like robust estimation, the quantile approach detects relationships missed by traditional data analysis. Robust estimates detect the influence of the bulk of the data, whereas quantile estimates detect the influence of co-variates on alternate parts of the conditional distribution. Applications of the quantile regression method can be found in Trzpiot (2008, 2009a, 2009b, 2010), Orwat-Acedańska and Trzpiot (2011), among others.

3.3. Quantile Spatial Autoregressive Model – QSAR model

The QSAR model of order τ blends the two approaches mentioned above. It can be written as follows (Trzpiot, 2012; Kostov, 2009):

$$\mathbf{Y} = \rho^{(\tau)}\mathbf{WY} + \mathbf{X}\boldsymbol{\beta}^{(\tau)} + \boldsymbol{\varepsilon}^{(\tau)}, \tag{8}$$

where $\mathbf{Y} \equiv Q_{(\tau)}(\mathbf{Y}|\mathbf{X})$, $\rho^{(\tau)}$ – quantile spatial autoregression parameter of order τ, $\boldsymbol{\beta}^{(\tau)}$ – vector of the model's parameters. Vector $\boldsymbol{\varepsilon}^{(\tau)}$ contains independent and identically distributed random variables whose distribution is not specified.

---

[5] The semi-parametric character of estimation of the model (6) follows from the fact that the error term distribution is left unspecified. Parametric approach is also available provided the error term follows asymmetric Laplace distribution.

Because of the endogeneity problems in models (8) and (3) – on the right hand side we have spatial lags of the dependent variable $\rho\mathbf{W}Y$ – their parameters are estimated using instrumental variables procedures (Chernozhukov and Hansen, 2006; Kim and Muller, 2004). In the paper, we use the procedure proposed by Kim and Muller (2004). It consists of the following steps:

1. Estimate the ordinary quantile regression model of order τ for **WY**:

$$\mathbf{WY} = \mathbf{X}\boldsymbol{\beta}^{*(\tau)} + \mathbf{WX}\boldsymbol{\gamma}^{*(\tau)} + \boldsymbol{\varepsilon}^{*(\tau)} \tag{9}$$

2. Calculate the predicted values from (8):

$$\widehat{\mathbf{W}\mathbf{Y}} = \mathbf{X}\hat{\boldsymbol{\beta}}^{*(\tau)} + \mathbf{WX}\hat{\boldsymbol{\gamma}}^{*(\tau)} \tag{10}$$

3. Use the predicted values as explanatory variable in the original model:

$$\mathbf{Y} = \rho^{(\tau)}\,\widehat{\mathbf{W}\mathbf{Y}} + \mathbf{X}\boldsymbol{\beta}^{(\tau)} + \boldsymbol{\varepsilon}^{(\tau)} \tag{11}$$

and estimate its parameters using another ordinary quantile regression by solving the optimization problem (7).

Applications of the spatial quantile regression method and the above procedure can be found in Trzpiot and Orwat-Acedańska (2016a, 2016b) among others.

4. EMPIRICAL ANALYSIS

4.1. Data, variables and empirical procedure

In the empirical part, we identify factors affecting the HLY in $n = 30$ European countries (27 EU members excluding Luxemburg, plus Iceland, Norway, and Switzerland which are associated with the EU). We work with yearly data and most of the series are taken from 2015.

The dependent variable in each of models under study is HLY (described in the second section). The HLY indicator is calculated for men (HLY_M) and women (HLY_W) separately. Selecting the potential exogenous variables, we focus on the health and lifestyle determinants and also on socio-economic factors. Eleven exogenous variables are studied for each country (Table 1).

Table 1

Exogenous variables used in the first step of the model (6) specification procedure

Variable	Symbol	Name	Description of the variable
X_1	AP	Air pollution	Carbon dioxide emission in tons per capita
X_2	E	Education	Fraction of population with tertiary education
X_3	GDP	GDP	GDP per capita
X_4	MD	Material deprivation	Fraction of population with four or more important housing items missing
X_5	SP	Social protection	Social protection expenditures to GDP
X_6	PD	Population density	Population density each of country
X_7	BH	Beds in hospitals	Beds in hospitals per 100000 inhabitants
X_8	D	Doctors	Doctors per 100,000 inhabitants
X_9	AC	Alcohol consumption	Alcohol consumption in liters per capita
X_{10}	C	Cigarettes	Fraction of regular smokers in population
X_{11}	OP	Obesity	Fraction of obese inhabitants in population

Source: own elaboration.

Most of the variables are taken from Eurostat. Some of them, mostly the health determinants, come from the WHO database. The completeness and reliability of the publicly available series served as the primary criteria for the selection of the explanatory variables. For example, the data on consumption of fruit and vegetables were not taken into account because of many missing entries that could not be substituted easily. Together with the constant term, matrix **X** has 12 columns and 31 rows. The parameters are estimated using QSAR model (8) for the nineteen quantiles: $\tau = 0.05$, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5, 0.55, 0.6, 0.65, 0.7, 0.75, 0.8, 0.85, 0.9, 0.95. The instrumental variables procedure, according to equations (9)-(11), proposed by Kim and Muller (2004) is employed. To build the weight matrix **W**, we utilize the inverse weight matrix: $w_{ij} = 1/d_{ij}$ if $i \neq j$ and $w_{ij} = 0$, otherwise, where d_{ij} denotes the distance between countries i and j. Confidence intervals and p-values are calculated using the residual bootstrap with 1000 subsamples. In the last step, the k-means algorithm is used to cluster the estimates obtained from the QSAR model for different quantiles. Computations are carried out in Matlab using the authors' own routines (for example, bootstrap estimation) as well as procedures written by Koenker and also LeSage (Spatial Econometric Toolbox). Statistica was used for clustering.

4.2. Results

The first part of empirical analysis focuses on point and interval estimation of the QSAR model (11) as well as significance testing of the estimates for different variants of the HLY measure for women:

$$\begin{aligned}\mathbf{HLY}_W^{(\tau)} = \rho^{(\tau)}\mathbf{W}\,\mathbf{HLY}_W + \beta_0^{(\tau)} + \beta_1^{(\tau)}\mathbf{AP} + \beta_2^{(\tau)}\mathbf{E} + \beta_3^{(\tau)}\mathbf{GDP} + \beta_4^{(\tau)}\mathbf{MD} + \\ +\beta_5^{(\tau)}\mathbf{SP} + \beta_6^{(\tau)}\mathbf{PD} + \beta_7^{(\tau)}\mathbf{BH} + \beta_8^{(\tau)}\mathbf{D} + \\ \beta_9^{(\tau)}\mathbf{AC} + \beta_{10}^{(\tau)}\mathbf{C} + \beta_{11}^{(\tau)}\mathbf{OP} + \boldsymbol{\varepsilon}^{(\tau)}.\end{aligned} \tag{12}$$

The following variables turned out to be insignificant for all of the studied quantiles: air pollution (AP), GDP, beds in hospitals (BH). We respecified the models by excluding those variables and we were left with the following models of HLY for women:

$$\begin{aligned}\mathbf{HLY}_W^{(\tau)} = \rho^{(\tau)}\mathbf{W}\,\mathbf{HLY}_W + \beta_0^{(\tau)} + \beta_1^{(\tau)}\mathbf{E} + \beta_2^{(\tau)}\mathbf{MD} + \beta_3^{(\tau)}\mathbf{SP} + \\ \beta_4^{(\tau)}\mathbf{PD} + \beta_5^{(\tau)}\mathbf{D} + \beta_6^{(\tau)}\mathbf{AC} + \mathbf{C}\beta_7^{(\tau)} + \beta_8^{(\tau)}\mathbf{OP} + \boldsymbol{\varepsilon}^{(\tau)}.\end{aligned} \tag{13}$$

The point estimates and the p-values of the significance tests are shown in Table 2.

The associated confidence intervals are depicted in Figure 1 where the solid lines represent the point estimates and the 90% confidence interval bounds are marked by the dotted lines.

The results after respecification of the HLY models for women show that the impact of the dependent variables varies with the quantile considered. In particular, the following regularities can be observed:

- In the group of the socio-economic variables (education, material deprivation, social protection, population density), education and material deprivation are statistically insignificant for quantiles of order 0.5–0.65. This means that they do not influence the length of healthy life in countries with the middle quantiles of the conditional distribution of HLY but are important for the other parts of the HLY distribution. The two remaining variables (social protection, population density) significantly impact all the conditional quantiles of the studied measure except for those of order 0.6–0.75.
- The factors associated with healthcare (number of doctors) and lifestyle (alcohol consumption, cigarettes, obesity) significantly affect HLY for all the studied quantile orders. Of course, the strength of the impact still varies with the quantile order.
- Spatial autoregression coefficients are statistically significant for all the studied quantiles which justifies accounting for the spatial effects in studying the factors affecting HLY for women.

Table 2

Estimates for HLY_w for different quantiles and p-values for respecified model (13)

	Education	Material deprivation	Social protection	Population density	Doctors	Alcohol	Cigarettes	Obesity	Autocorr. coefficient
Symbol	E	MD	SP	PD	D	AC	C	OP	
Quantile	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	ρ
0.05	0.221	0.306	-0.047	0.006	0.033	-0.505	-0.259	-0.507	0.674
0.1	0.221	0.306	-0.047	0.006	0.033	-0.505	-0.259	-0.507	0.674
0.15	0.221	0.306	-0.047	0.006	0.033	-0.505	-0.259	-0.507	0.674
0.2	0.197	0.192	-0.335	0.007	0.043	-0.417	-0.282	-0.527	0.771
0.25	0.249	0.162	-0.339	0.005	0.036	-0.578	-0.233	-0.637	0.771
0.3	0.234	0.131	-0.374	0.006	0.038	-0.541	-0.232	-0.612	0.788
0.35	0.242	0.124	-0.405	0.006	0.038	-0.632	-0.227	-0.617	0.813
0.4	0.231	0.038	-0.319	0.005	0.026	-0.662	-0.115	-0.784	0.764
0.45	0.141	-0.043	-0.232	0.004	0.020	-0.612	-0.063	-0.978	0.715
0.5	0.057	-0.080	-0.198	0.003	0.020	-0.566	-0.072	-1.090	0.698
0.55	0.064	-0.084	-0.199	0.003	0.020	-0.623	-0.030	-1.037	0.707
0.6	0.038	0.092	-0.075	0.001	0.023	-0.884	-0.113	-1.319	0.622
0.65	0.044	0.144	0.141	0.002	0.022	-0.812	-0.103	-1.381	0.494
0.7	0.047	0.140	0.141	0.002	0.022	-0.809	-0.101	-1.387	0.490
0.75	0.182	0.101	-0.040	0.004	0.023	-0.341	-0.151	-0.985	0.609
0.8	0.111	0.071	-0.050	0.005	0.024	-0.176	-0.080	-0.620	0.708
0.85	0.119	0.060	-0.082	0.004	0.027	-0.285	-0.112	-0.632	0.739
0.9	0.119	0.060	-0.082	0.004	0.027	-0.285	-0.112	-0.632	0.739
0.95	0.119	0.060	-0.082	0.004	0.027	-0.285	-0.112	-0.632	0.739
Quantile	*p*-values *								
0.05	**0**	**0**	0.2	**0**	**0**	**0.1**	**0**	**0.1**	**0**
0.1	**0**	**0**	0.2	**0**	**0**	**0.1**	**0**	**0.1**	**0**
0.15	**0**	**0**	0.4	**0.05**	**0.05**	**0.05**	**0**	**0.1**	**0**
0.2	**0.1**	**0**	**0.05**	**0.1**	**0**	**0.05**	**0**	**0**	**0**
0.25	**0.05**	**0**	**0**	**0.05**	**0**	**0.05**	**0**	**0**	**0**
0.3	**0.05**	**0.1**	**0.05**	**0.05**	**0**	**0**	**0**	**0**	**0**
0.35	**0**	**0.1**	**0.05**	**0**	**0**	**0**	**0**	**0**	**0**
0.4	**0**	0.25	**0.05**	**0**	**0**	**0**	**0**	**0**	**0**
0.45	**0.1**	0.5	**0.1**	**0**	**0**	**0**	**0.05**	**0**	**0**
0.5	0.4	0.35	**0**	0.15	**0**	**0**	**0.05**	**0**	**0**
0.55	0.5	0.35	**0.05**	0.25	**0**	**0**	**0.1**	**0**	**0**
0.6	0.4	0.25	0.3	0.4	**0**	**0**	**0**	**0**	**0**
0.65	0.5	**0.1**	0.25	0.35	**0**	**0**	**0.05**	**0**	**0**
0.7	0.45	**0.1**	0.25	0.5	**0**	**0**	**0**	**0**	**0**
0.75	**0**	**0.1**	0.4	0.15	**0.05**	0.15	**0**	**0**	**0**
0.8	0.15	0.25	0.35	*0.05*	**0.05**	0.3	0.2	**0**	**0**
0.85	0.15	0.2	0.45	0.15	**0**	0.25	**0.05**	**0**	**0**
0.9	**0.05**	0.2	0.3	**0.1**	**0**	0.2	**0.1**	**0**	**0**
0.95	**0.05**	0.3	0.15	0.15	**0**	0.2	**0.1**	**0**	**0**

* The estimates in bold are statistically significant ($\alpha = 0.1$)

Source: own calculation.

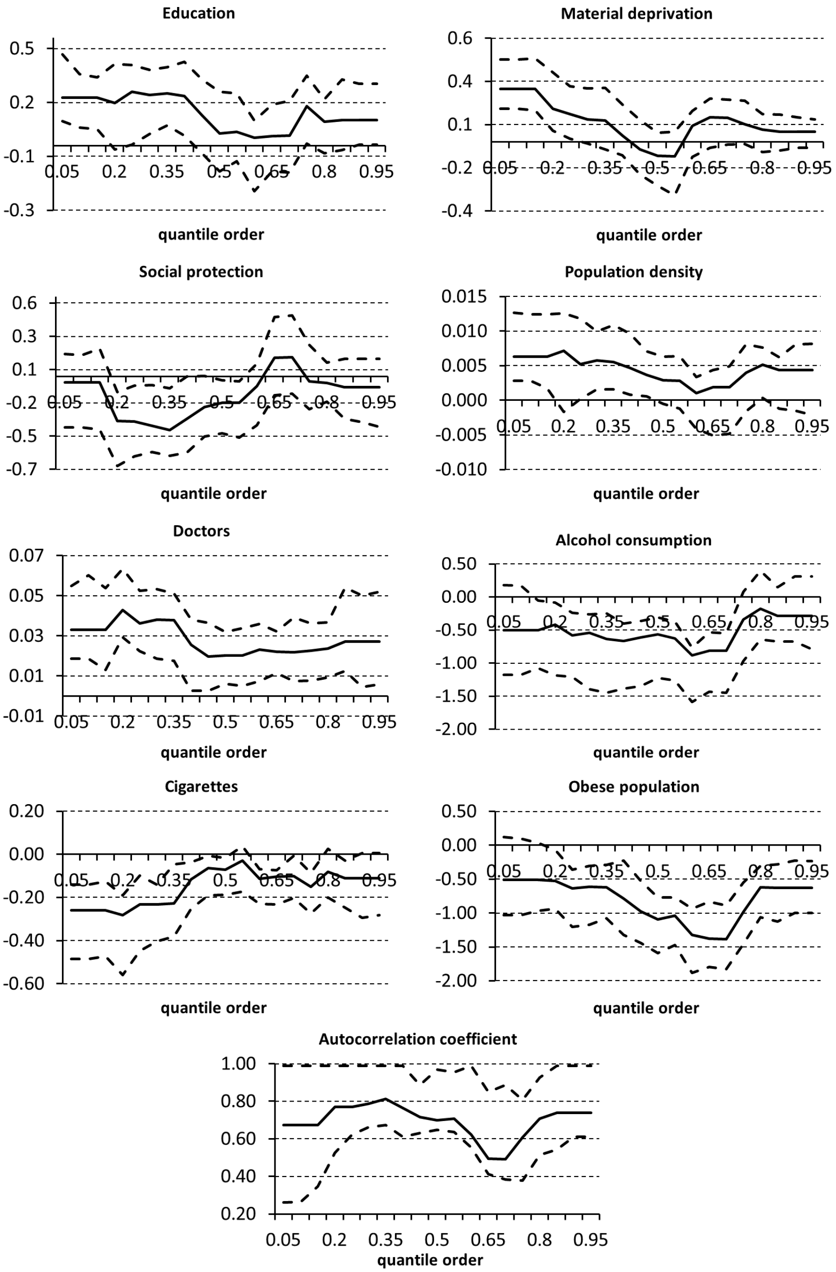

Figure 1. Parameter estimates with 90% confidence intervals for model (13)

Source: own calculation.

In the next step of the empirical analysis, we clustered the estimates obtained from the model (13) for the different quantiles using the k-means algorithm. The number of groups was set to three. As a result, we obtained the clusters whose compositions and distances of its members from the group centers are presented in Table 3.

Table 3

Clusters and distances from their centers for the estimates obtained from model (13) for the different quantiles

Cluster 1*		**Cluster 2***		**Cluster 3***	
Quantile	**Distance**	**Quantile**	**Distance**	**Quantile**	**Distance**
0.45	0.1102	0.75	0.1069	0.05	0.0850
0.50	0.0887	0.80	0.0472	0.10	0.0850
0.55	0.0912	0.85	**0.0256**	0.15	0.0850
0.60	**0.0777**	0.90	**0.0256**	0.20	0.0633
0.65	0.1121	0.95	**0.0256**	0.25	**0.0438**
0.70	0.1129			0.30	0.0536
				0.35	0.0722
				0.40	0.1109

* In bold are the quantiles for which the estimates are closest to the cluster center

Source: own calculation.

The first cluster contains the estimates obtained for quantiles of orders 0.45–0.70. Therefore, the cluster summarizes the impact of the factors on the middle quantiles of the conditional distribution of HLY. In all the models that form the cluster, the healthcare and the lifestyle-related variables (doctors, alcohol consumption, cigarettes, obesity) are statistically significant. The estimates for quantile of order 0.6 can be considered as representative for the cluster because it is located closest to its center. The representative estimated model takes the following form[6]:

$$\mathbf{HLY}_W^{(0.6)} = 0.62\,\mathbf{W}\,\mathbf{HLY}_W + 0.06\,\mathbf{D} - 0.88\,\mathbf{AC} - 0.11\,\mathbf{C} - 1.32\,\mathbf{OP}. \quad (14)$$

The **second cluster** consists of the estimates obtained from the models for the highest quantile orders 0.75–0.95. The estimates for the orders of

[6] For clarity, equations (14)–(16) do not contain the variables that turned out insignificant after the respecification. Of course, further respecification of the models would change the estimates again.

0.85, 0.9, and 0.95 are equal and can be considered as the representative for the cluster. For example, it takes the following form:

$$\mathbf{HLY}_W^{(0.9)} = 0.74\mathbf{W}\ \mathbf{HLY}_W + 0.12\ \mathbf{E} + 0.004\,\mathbf{PD} - 0.27\ \mathbf{D} - 0.11\ \mathbf{C} - 0.63\mathbf{OP}. \tag{15}$$

The second cluster is characterized by relatively high differentiation as far as the significance of the variables is considered. In most of the models all the variables related to healthcare and lifestyle are significant.

The last cluster is the most numerous one and identifies the factors affecting the conditional quantiles of the low orders. Apart from the estimates for the lowest quantile orders (0.05–0.15) where social protection does not play a significant role in explaining the observed differences in HLY, all the considered variables significantly influence the response. The estimates for the quantile order of 0.25 given by equation (16) are closest to the cluster's center.

$$\begin{aligned}\mathbf{HLY}_W^{(0.25)} = {} & 0.77\mathbf{W}\ \mathbf{HLY}_W + 0.25\mathbf{E} + 0.16\mathbf{M} - 0.34\mathbf{SP} + \\ & 0.005\mathbf{PD} + 0.03\mathbf{D} - 0.58\mathbf{AC} - 0.23\mathbf{C} - 0.64\mathbf{OP}.\end{aligned} \tag{16}$$

A similar analysis was performed for men. In the first step, we estimated the QSAR model (17) for nineteen different quantile orders:

$$\begin{aligned}\mathbf{HLY}_M^{(\tau)} = {} & \rho^{(\tau)}\mathbf{W}\ \mathbf{HLY}_M + \beta_0^{(\tau)} + \beta_1^{(\tau)}\mathbf{AP} + \beta_2^{(\tau)}\mathbf{E} + \beta_3^{(\tau)}\mathbf{GDP} + \\ & \beta_4^{(\tau)}\mathbf{MD} + \beta_5^{(\tau)}\mathbf{SP} + \beta_6^{(\tau)}\mathbf{PD} + \beta_7^{(\tau)}\mathbf{BH} + \beta_8^{(\tau)}\mathbf{D} + \\ & \beta_9^{(\tau)}\mathbf{AC} + \beta_{10}^{(\tau)}\mathbf{C} + \beta_{11}^{(\tau)}\mathbf{OP} + \boldsymbol{\varepsilon}^{(\tau)}.\end{aligned} \tag{17}$$

The models were subsequently respecified keeping only six variables that were statistically significant for most of the quantiles. The final model takes the following general form:

$$\begin{aligned}\mathbf{HLY}_M^{(\tau)} = {} & \rho^{(\tau)}\mathbf{W}\ \mathbf{HLY}_M + \beta_0^{(\tau)} + \beta_1^{(\tau)}\mathbf{E} + \beta_2^{(\tau)}\mathbf{PD} + \beta_3^{(\tau)}\mathbf{D} + \\ & + \beta_4^{(\tau)}\mathbf{AC} + \beta_5^{(\tau)}\mathbf{C} + \beta_6^{(\tau)}\mathbf{OP} + \boldsymbol{\varepsilon}^{(\tau)}.\end{aligned} \tag{18}$$

The estimates obtained from model (18) are shown in Table 4.

After respecification, only education and population density from the group of socio-economic indicators remained statistically significant for most of the quantiles in the first step of the model specification procedure. On the other hand, all the healthcare- and lifestyle-related variables were

Table 4

Estimates for HLY_M for different quantiles and p-values for model (18)

	Education	**Population density**	**Doctors**	**Alcohol**	**Cigarettes**	**Obesity**	**Autocorr. coefficient**
Symbol	E	PD	D	AC	C	OP	
Quantile	β_1	β_2	β_3	β_4	β_5	β_6	ρ
0.05	0.157	0.004	0.035	-0.720	-0.179	-0.640	0.685
0.1	0.157	0.004	0.035	-0.720	-0.179	-0.640	0.685
0.15	0.146	0.007	0.035	-0.630	-0.169	-0.604	0.672
0.2	0.261	0.004	0.016	-1.023	-0.020	-0.464	0.795
0.25	0.140	0.006	0.010	-0.553	0.027	-0.368	0.821
0.3	0.156	0.007	0.011	-0.602	0.016	-0.457	0.788
0.35	0.164	0.006	0.012	-0.674	-0. 018	-0.557	0.782
0.4	0.160	0.006	0.017	-0.628	-0.052	-0.623	0.741
0.45	0.144	0.004	0.021	-0.851	-0.066	-0.727	0.750
0.5	0.183	0.004	0.022	-0.955	-0.111	-0.756	0.767
0.55	0.180	0.004	0.024	-0.956	-0.161	-0.572	0.852
0.6	0.170	0.003	0.025	-1.045	-0.185	-0.739	0.819
0.65	0.153	0.005	0.027	-0.771	-0.124	-0.315	0.888
0.7	-0.034	0.002	0.023	-0.825	-0.152	-0.467	0.988
0.75	-0.089	0.002	0.038	-0.853	-0.149	-0.476	0.922
0.8	-0.051	0.000	0.028	-1.054	-0.095	-0.854	0.830
0.85	-0.075	0.002	0.041	-0.608	-0.248	-0.476	0.906
0.9	0.055	0.003	0.015	-0.830	-0.124	-0.450	0.990
0.95	0.052	0.003	0.017	-0.822	-0.121	-0.416	0.990
Quantile	p-values *						
0.05	**0.1**	**0.05**	**0**	**0**	**0.05**	**0**	**0**
0.1	**0.05**	**0.05**	**0**	**0**	**0**	**0**	**0**
0.15	**0**	**0.05**	**0**	**0**	**0.05**	**0**	**0**
0.2	**0**	0.2	**0.1**	**0**	0.3	**0.05**	**0**
0.25	0.15	**0.05**	0.2	**0**	0.4	**0.05**	**0**
0.3	**0.05**	**0**	0.15	**0**	0.4	**0**	**0**
0.35	**0.1**	**0**	**0.1**	**0.05**	0.4	**0**	**0**
0.4	**0.05**	**0**	**0**	**0**	0.2	**0**	**0**
0.45	**0.05**	0.15	**0**	**0**	0.25	**0**	**0**
0.5	0.15	0.2	**0**	**0**	**0.05**	**0**	**0**
0.55	0.15	0.2	**0**	**0**	**0.05**	**0**	**0**
0.6	**0.1**	0.15	**0**	**0**	**0.05**	**0**	**0**
0.65	0.15	**0.1**	**0**	**0**	**0.05**	**0.05**	**0**
0.7	0.35	0.25	**0**	**0**	**0**	**0.05**	**0**
0.75	**0.05**	0.4	**0**	**0**	**0.05**	**0**	**0**
0.8	0.15	0.5	**0**	**0**	**0.05**	**0**	**0**
0.85	0.3	0.35	**0**	**0.1**	**0.05**	**0**	**0**
0.9	0.55	0.3	**0**	**0**	**0.05**	**0**	**0**
0.95	0.65	0.35	**0.05**	**0**	**0.05**	**0**	**0**

* The estimates in bold are statistically significant ($\alpha = 0.1$)

Source: own calculation.

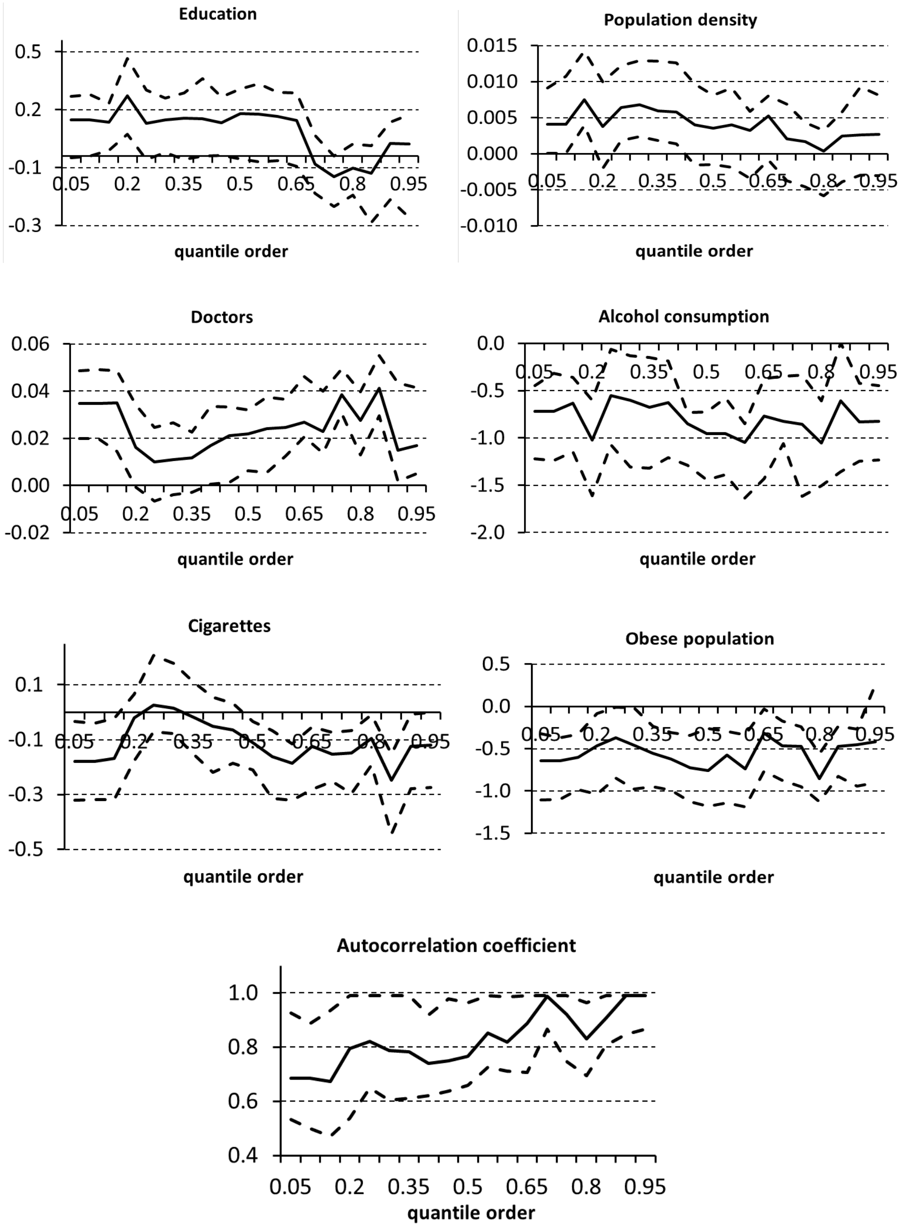

Figure 2. Parameter estimates with 90% confidence intervals for model (18)

Source: own calculation.

considered in the second step because they significantly affected the majority of the studied quantiles of HLY in the initial specification step. In general the results show, similarly to what is observed for women, that the impact of the considered variables on HLY differs as far as different quantile orders are concerned.

In particular, the following patterns can be observed in Figure 2:

- Education and population density do not play a significant role for the quantiles of order higher than 0.5. They do influence the remaining parts of the HLY distribution.
- The variables related to healthcare and lifestyle show a significant relationship with HLY in all the studied models (cigarettes is the only exception here; it is insignificant for the quantiles of order 0.2–0.45, which can be related to countries with a modest HLY level).

We clustered the obtained estimates into three groups using the *k*-means method. The composition of the clusters is presented in Table 5.

Table 5

Clusters and distances from their centers for the estimates obtained from model (18) for the different quantiles

Cluster 1*		**Cluster 2***		**Cluster 3***	
Quantile	Distance	Quantile	Distance	Quantile	Distance
0.65	0.0768	0.45	0.0579	0.05	0.0615
0.70	0.0279	0.50	**0.0341**	0.10	0.0615
0.75	0.0526	0.55	0.0539	0.15	0.0427
0.80	0.1108	0.60	0.0477	0.20	0.1089
0.85	0.0909			0.25	0.0963
0.90	0.0297			0.30	0.0589
0.95	**0.0271**			0.35	**0.0281**
				0.40	0.0307

* In bold are the quantiles for which the estimates are located the closest to the cluster center

Source: own calculation.

The first cluster consists of the estimates for the quantiles of order 0.65–0.95. All the variables associated with healthcare and lifestyle play a statistically important role in explaining the differences in HLY for men.

The model for the quantile of order 0.95 can be considered as the representative for the cluster. It takes the following form:[7]

$$\mathbf{HLY}_M^{(0.95)} = 0.99\mathbf{W}\,\mathbf{HLY}_M + 0.01\,\mathbf{D} - 0.82\,\mathbf{AC} - 0.12\,\mathbf{C} - 0.41\,\mathbf{OP}. \quad (19)$$

The second cluster contains the estimates from the models for the quantiles of orders 0.45–0.6. The relationship for these countries can be represented by the median model which takes the following form:

$$\mathbf{HLY}_M^{(0.5)} = 0.76\mathbf{W}\,\mathbf{HLY}_M + 0.02\,\mathbf{D} - 0.95\,\mathbf{AC} - 0.11\,\mathbf{C} - 0.75\,\mathbf{OP}. \quad (20)$$

Finally, the last cluster comprises the estimates for the lowest quantiles of orders 0.05–0.4. Almost all the variables are statistically significant. In particular, the socio-economic variables like education level and population density, the healthcare characteristic – number of doctors – as well as lifestyle represented by alcohol consumption, cigarettes and obesity, all significantly affect the lowest quantiles of the conditional HLY distribution. The model for the quantile of order 0.35 can be considered as the representative for the cluster. It takes the following form:

$$\begin{aligned}\mathbf{HLY}_M^{(0.35)} = 0.78\mathbf{W}\,\mathbf{HLY}_M + 0.16\,\mathbf{E} + 0.0056\,\mathbf{PD} + \\ + 0.118\,\mathbf{D} - 0.674\,\mathbf{AC} - 0.557\,\mathbf{OB}.\end{aligned} \quad (21)$$

CONCLUSION

We have studied the potential determinants of the healthy life years of men and women in the EU: six socio-economic, two healthcare and three lifestyle attributes. After respecification and removing the insignificant factors, the new QSAR estimates for different quantiles were clustered in three groups using the *k*-means algorithm.

The results of the whole procedure show that the impact of the determinants on different quantiles of the conditional distribution of HLY (of both, men and women) varies. Moreover, the spatial autocorrelation coefficients are always statistically significant.

The clustering procedure reveals that for women, the quantiles below the median are significantly affected by all the studied groups of factors: socio-economic (education, material deprivation, social protection, population

[7] As for women, equations (19)–(21) do not contain the variables that turned out insignificant after the respecification. Of course, further respecification of the models would change the estimates again.

density), healthcare (doctors) and lifestyle (alcohol consumption, cigarettes, obesity). The middle quantiles are primarily correlated with healthcare (doctors) and lifestyle (alcohol consumption, cigarettes, obesity) factors. The similar factors also play a significant role in explaining the behavior of the highest quantiles of the conditional distribution of HLY. For men, the lowest quantiles are correlated with socio-economic (education, population density), healthcare (doctors), and lifestyle (alcohol consumption, cigarettes, obesity) factors. The quantiles of the middle and the high orders are mostly affected by healthcare (doctors) and lifestyle (alcohol consumption, cigarettes, obesity) factors.

To sum up, regardless of the quantile order, HLY in the EU is significantly related to healthcare and lifestyle factors. However, in many cases, the socio-economic circumstances (like education and material deprivation) also affect the variable under study. These results confirm the hypothesis studied in the paper that the spatial autocorrelation models for healthy life years should be estimated and interpreted using quantile regression.

REFERENCES

Anselin, L., *Spatial Econometrics: Methods and Models*. Springer, Netherlands, 1998.

Bengtsson, T., Scott, K., *Population aging and the future of the welfare state: the example of Sweden,* “Population and Development Review”, 37, pp. 158–70, 2011.

Brønnum-Hansen, H., *Socially disparate trends in lifespan variation: A trend study on income and mortality based on the nationwide Danish register data*, BMJ Open, Vol. 7, Issue 5, 2017.

Cambois, E., Blachier, A., Robine, J.-M., *Aging and health in France : An unexpected expansion of disability in mid-adulthood over recent years*, “European Journal of Public Health”, Vol. 23, Issue 4, pp. 575–581, 2013.

Cambois, E., Robine, J.-M., *Healthy life expectancy in Europe*, “Population and Societies”, p. 499, 2013.

Charafeddine, R., Gadeyne, S., Deboosere, P., Berger, N., Demarest, S., Van Oyen, H., *Social inequalities in Healthy Life Expectancy. Alternative methods of estimation in the absence of the national census*. WIV-ISP, Direction Opérationnelle Santé Publique et Surveillance, Bruxelles, 2011.

Chernozhukov, V., Chansen, C., *Instrumental Quantile Regression Inference for Structural and Treatment Effect Models*, “Journal of Econometrics”, 127, pp. 491–525, 2006.

Doblhammer, G., Kytir, J., *Social inequalities in disability-free and healthy life expectancy in Austria*, “Wiener klinische Wochenschrift”, 110(11), pp. 393–396, 1998.

Dubkova, N., Krumins, J., *Life expectancy and health expectancy in Latvia: Changes and interpretation problems*. Research Papers of the Central Statistical Bureau of Latvia, Riga, pp. 21–33, 2012.

Fouweather, T., Gillies, C., Wohland, P., Van Oyen, H., Nusselder, W., Robine, J.-M., Cambois, E., Jagger, C., *Comparison of socio-economic indicators explaining inequalities in Healthy Life Years at age 50 in Europe: 2005 and 2010*, "European Journal of Public Health", 25(6), pp. 978–83, 2015.

Frova, L., Battisti, A., Burgio, A., *Are gaps in disability free life expectancies diminishing in Italy*? European Journal of Ageing, 7, pp. 239–247, 2010.

Gromulska, L., Wysocki, M., Goryński, P., *Lata przeżyte w zdrowiu (Healthy Life Years, HLY) – zalecany przez Unię Europejską syntetyczny wskaźnik sytuacji zdrowotnej ludności* [*Healthy Life Years, HLY – A synthetic indicator of the population's health situation recommended by the European Union*], "Przegląd Epidemiologiczny", 62(4), pp. 811–820, 2008.

Gutiérrez-Fisac, J. L., Regidor, E., Alfaro, M., *Healthy Life Expectancies in Spain 1986–2007.Disability-free life expectancy and life expectancy in good perceived health in Spain and its autonomous communities*. Ministry of Health, Social Policy and Equality, Madrid 2010.

Jagger, C., EHEMU team., 2006, *Healthy life expectancy in the EU 15*, [in:] *Living longer but healthier lives: How to achieve health gains in the elderly in the European Union*, Europe Blanche XXVI, Institut des Sciences de la Santé, pp. 49–62.

Jagger, C., Gillies, C., Mascone, F., Cambois, E., Van Oyen, H., Nusselder, W. J., Robine, J.-M., *Inequalities in healthy life years in the 25 countries of the European Union in 2005: a cross-national meta-regression analysis*, "The Lancet", 372(9656), pp. 2124–2131, 2008.

Kim, T. H., Muller, C., *Two-stage Quantile Regression When the First Stage is Based on Quantile Regression*, "Econometrics Journal", 7, pp. 218–231, 2004.

Koenker, R., Bassett, B., *Regression Quantiles*, "Econometrica", 46, pp. 33–50, 1978.

Kostov, P., *A Spatial Quantile Regression Hedonic Model of Agricultural Land Prices*, "Spatial Economic Analysis", 4(1), pp. 53–72, 2009.

Lee, L. F., *Consistency and Efficiency of Least Squares Estimation for Mixed Regressive, Spatial Autoregressive Models*, "Econometric Theory", 18(02), pp. 252–277, 2002.

Lee, L. F., *GMM and 2sls Estimation of Mixed Regressive, Spatial Autoregressive Models,* "Journal of Econometrics", 137, pp. 489–514, 2007.

LeSage, J., *Bayesian Estimation of Spatial Autoregressive Models*, "International Regional Science Review", 20(1–2), pp. 113–129, 1997.

LeSage, J. P.; Pace, R. K., Introduction to Spatial Econometrics, Chapman and Hall, CRC, New York 2009.

Lum, K., Gelfand A., *Spatial Quantile Multiple Regression Using the Asymmetric Laplace Process*, "Bayesian Analysis", 7 (2), pp. 235–258, 2012.

Majer, I. M., Stevens, R, Nusselder, W. J., Mackenbach, J. P., van Baal, P. H., *Modeling and forecasting health expectancy: theoretical framework and application*, "Demography", 50(2), pp. 673–697, 2013.

Olatunde, O., Smith, M., White, C., *Life expectancy and disability-free life expectancy estimates for Middle Super Output Areas*; *England, 1999-2003,* "Health Statistics Quarterly", 47, pp. 33–65, 2010.

Orwat-Acedańska, A., Trzpiot, G., *The Classification of Polish Mutual Balanced Funds on the Management Style – Quantile Regression Approach*, "Theory and Applications of Quantitative Methods, Econometrics" 31, University of Economics in Wrocław, 194, pp. 9–23, 2011.

Perenboom, P., van Oyen, H., Mutafova, M. N., *Health expectancies in European countries*, [in:] Robine, J.-M., Jager, C., Mathers, C. D, Crimmins, E. M., Suzman, R. M. (eds), *Determining Health Expectancies*, chapter 18. John Wiley & Sons, Ltd, Chichester, UK, 2003.

Petrauskiène, J., Ambrozaitiene, D., Kalediene, R., Starkuviène, S., *Assessment of disability-free life expectancy in Lithuania*, Medicina (Kaunas), 46(10), pp. 707–711, 2010.

Portnoy, S., Koenker, R., *The Gaussian Hare and the Laplacian Tortoise: Computability of Squared-Error Versus Absolute-Error Estimators, with Discussion*, "Statistical Science", 12(4), pp. 279–300, 1997.

Robine, J.-M., *Summarizing Health Status* [in:] Pencheon, D., Guest, C., Melzer, D., Gray, J. A. M., *Oxford Handbook of Public Health Practice*, 2nd ed. Oxford University Press, 2006.

Robine, J.-M., Jagger, C., Euro-REVES, *Creating a coherent set of indicators to monitor health across Europe: the Euro-REVES 2 project*, "European Journal of Public Health", 13(3), pp. 6–14, 2003.

Robine, J.-M., Jagger, C., Mathers ,C. D., Crimmins, E. M., Suzman, R. M., *Determining health expectancies*. Wiley, Chichester, UK, 2003.

Robine, J.-M., Jagger, C., Egidi, V., *Selection of a Coherent Set of Health Indicators. A First Step Towards A User's Guide to Health Expectancies for the European Union*, Euro-REVES, 2000.

Suchecki, B. (ed.), *Ekonometria przestrzenna. Metody i modele analizy danych przestrzennych* [*Spatial econometrics. Methods and models for spatial data analysis*]. Wydawnictwo C. H. Beck, Warsaw 2010.

Sullivan, D. F., *A single index of mortality and morbidity*. HSMHA Health Reports, 86, pp. 347–354, 1971.

Trzpiot, G., *Implementacja metodologii regresji kwantylowej w estymacji VaR* [*The implementation of quantile regression methodology in VaR estimation*], Studia i Prace Wydziału Nauk Ekonomicznych i Zarządzania, University of Szczecin, No. 9, pp. 316–323, 2008.

Trzpiot, G., *Model regresji kwantylowej a estymacja modelu czynnikowego* [*Quantile regression model versus factor model estimation*], Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu, Inwestycje finansowe i ubezpieczenia – tendencje światowe a polski rynek, No. 60, pp. 469–479, 2009a.

Trzpiot, G., *Estimation Methods for Quantile Regression*, Studia Ekonomiczne. Zeszyty Naukowe, Akademia Ekonomiczna im. Karola Adamieckiego w Katowicach, 53, pp. 81–90, 2009b.

Trzpiot, G., *Model regresji kwantylowej relacji stopa zwrotu – zmienność dla wybranych indeksów z GPW w Warszawie* [*Quantile regression model of return rate – volatility relation for some Warsaw Stock Exchange indexes*], Zeszyty Naukowe Uniwersytetu Szczecińskiego. Finanse, Rynki Finansowe, Ubezpieczenia, No. 28, pp. 61–76, 2010.

Trzpiot, G., *Spatial Quantile Regression,* Comparative Economic Research, 15, 4, pp. 265–279, University of Łódź, 2012.

Trzpiot, G., Orwat-Acedańska A., *Spatial Quantile Regression in Analysis of Mortality*, "Acta Universitatis Lodziensis, Folia Oeconomica", 5(325), pp. 181–196, 2016a.

Trzpiot, G., Orwat-Acedańska A, *Spatial Quantile Regression in Healthy Life Years in UE Countries*, "Comparative Economic Research", 19, 5, pp.179–199, 2016b.

Van Oyen, H., Cox, B., Demarest, S., Deboosere, P., Lorant, V., *Trends in health expectancy indicators in the older adult population in Belgium between 1997 and 2004*, "European Journal of Ageing", 5(2), pp. 137–146, 2008.

Vrabcová, J., Daňková, Š., Faltysová, K., *Healthy Life Years in the Czech Republic: different data sources, different figures*, "Demografie", 59(4), pp. 315–331, 2017.

Wróblewska, W., *Sumaryczne miary stanu zdrowia populacji* [*Summary measures of population health*], „Studia Demograficzne", No. 1–2(153–154), pp. 153–154, 2008.

Received: December 2017, revised: July 2018