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# THE WELLBEING EFFECT OF COMMUNITY DEVELOPMENT. SOME MEASUREMENT AND MODELING ISSUES[1]

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## ABSTRACT

The two interconnected methodological tasks – measurement and modeling – become especially challenging in the context of exploration of the interaction between the local community development and individual wellbeing. In this paper, the preliminary results illustrate usefulness of an analytical framework aimed to assess an impact of the local development on individual wellbeing through multilevel modeling, accounting for spatial effects is. To this aim, a dual measurement system is employed with data from two independent sources: (i) the Local Data Bank (LDB) for calculating a multidimensional index of local deprivation (MILD), and to capture variations in geographically embedded administrative units, communes (the country's finest division), and (ii) the Time Use Survey data to construct the U-index ('unpleasant'), considered as a measure of individual wellbeing. Since one of the implications of the main hypothesis on the interaction between community development and individual wellbeing was the importance of 'place' and 'space' (effect of neighborhood and proximity), a special emphasize has been put on spatial effects, i.e. geographic clusters and spatial associations (autocorrelation, dependence The evidence that place and space matter for this relationship provides support for validity of both multilevel and spatial approaches (ideally, combined) to this type of problems.

## I. Introduction

### *Background and problem*

Although the view that *place* and *space* matter for both the community and individual wellbeing is widely shared among the analysts and experts interested in their improvement (separately or jointly), a little effort has been done so far to determine what type of functional form describes the relationships or mutual influence between the two kinds of wellbeing, including their spatial patterns and factors of dynamics. This research was motivated as much by the knowledge gap in the literature concerning this methodological issue, including the ways of

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parameterization of these relationships, as also by the policy practitioners' demand (addressed to statisticians) for tooling devices to better allocate the scare resources to local communities while accounting for individual wellbeing. It embraces exploration of the relationships between subjective and objective measures of wellbeing at micro- (individual) and macro- (community) level while accounting for their cross-level operating factors in the presence of spatial effects, including quality of the place and spatial dependency.

Since the relationship between community wellbeing (CWB) and individual wellbeing (IWB) is of particular interest here, the three kinds of intertwined issues must be addressed concurrently: measurement – data – models. The measurement problem is complicated by the fact that, as noted by Gibson (2016), there is no theoretical justification for maximizing either happiness or life satisfaction, because neither corresponds to *utility* (p. 439). *'Happiness* is not all that matters, but first of all, it does matter (…), and second, it can often provide useful evidence on whether or not we are achieving our objectives in general' (Sen, 2008). However, an alternative approach, *Sen's capability approach,* which stresses priority of *functionings* and *capabilities* instead of resources or utility is becoming more useful also for policy purposes (Alkire, 2015): "The need for identification and valuation of the important functionings cannot be avoided by looking at something else, such as happiness, desire fulfillment, opulence, or command over primary goods' (Sen 1985 – in Alkire, op cit., p.1).Therefore, different information sources, including subjective data, can provide better insights on values and perceptions of people.

Within such a type of analytical framework, an ideal strategy seems to be the multilevel spatial modeling. However, some restrictions related to availability of data – which are here *ad hoc* combined from different sources instead to be generated by design to have the appropriate nested (hierarchical) structure - the cross-level modeling methodology will be illustrated below in a simplified version. Both types of possible strategies are explored and will be demonstrated as complementary to each other, 'interactive' and 'structural'. The former being focused on assessing the effect of interaction in searching for sources of variability at both individual and community levels. The latter is aimed at identifying causal *mediator* in searching for sources of influence (direct and indirect impact).

Analyses conducted in this paper use the multi-source database constructed through 'integrating' data – i.e. matching them on the ground of commune (*gmina*) – from three different sources: the Local Data Bank (public data file), the Time Use Survey (TUS, carried out by the Central Statistical Office in 2013), and Social Diagnosis (representative survey conducted this same year by an independent academic consortium). The measures derived from these data sets made it possible to explore spatial patterns of associations, autocorrelations and the dependency between measures of local deprivation (gmina-level) and the TUS-based indicators of wellbeing (the so-called index of 'unpleasant state', U-index). Although the results are preliminary and hardly robust - given incidental rather than natural hierarchically structured spatially distributed data, used in this study - they firmly support the adopted approach, i.e. employing spatially integrated social research framework for both analytical and policy purposes as a 'good practice' (methodologically) whenever place and space matter.

The paper is structured as follows. In the next section presented are some conceptual and measurement issues of key variables. It is followed by discussion (in section 3) of cross-level interrelation models, along with empirical results of their application. The explicitly included spatial aspects and spatial analysis of geo-referenced data, along with preliminary results are discussed in section 4. The concluding section closes up the paper, with some suggestions on prospective directions of further investigations.

## II. The conceptualization, measurement and modeling of wellbeing

Conceptualization, *operationalization* and the measurement of wellbeing typically start with questions *what?, how?* and *why?* Consequently, the three types of issues – *measurement, data* and *modeling*- need to be considered concomitantly. Such an approach is adopted in the form of a perspective of spatially integrated social research within a multilevel spatial analytical framework capable of guiding methodological choices for selecting and integrating the needed data from different sources

While focusing on functionings as things that people actually value, one may consider using data from time use survey in which respondent is asked to report what s/he did in the previous day - Day Reconstruction Method (Kahneman et al., 2004) [4]. Respondent makes also an assessment of the time spent on performing particular activity as pleasant or unpleasant (the so-called 'time of unpleasant state', Krueger et al., 2009). This approach is the key for constructing individual wellbeing measure here. It converges with conceptualizations of subjective wellbeing that take into account both positive and negative affectivity (Bradburn 1969) associated with the performed activity, and is now common in empirical research following international recommendations for measuring subjective wellbeing in public statistics (OECD 2013; NRS 2013; Kalton, Mackie, Okrasa 2015; Maggino 2017).

The key importance of community wellbeing in both research and policy considerations of the individual wellbeing determinants, especially in the development context (with clear distinction between local and regional development, e.g. Capello, 2009) is due to several reasons. Many of them have been recognized and discussed thoroughly in the literature, either as a part of the process or of outcome of such development, challenging the traditional use of GDP and other economic indicators as measures of social progress (Stiglitz et al., 2010, OECD, 2013, Kim and Ludwigs, 2017; Lee et al., 2015). Methods of community wellbeing assessment, including subjective aspects of wellbeing, are becoming standard tools for policy purposes in several countries (notably in Australia, Canada, USA and UK). They all have one feature in common, namely, they are based on self-reported feeling about selected aspects of wellbeing in connection with community, and community itself is among the components of the wellbeing measures.

One special feature of local community that affects its wellbeing in the development context is community cohesion. It is interpreted here in a broader

[4] "Functionings is a broad term used to refer to the activities and situations that people spontaneously recognize to be important" (Alkire, op cit, p. 3-4).

sense than the latter – hence termed *spatial cohesion* - due to embracing all other types of cohesion: social, economic or territorial cohesion, which are typically considered among the goals of the European Union's development policies and studies (focused often on so-called *β-convergence and σ-convergence,* respectively). Usually, it is meant consistently with classical interpretation of the term, e.g. following Forrest's and Kearns' (2001) specification of the component topic areas: (I) *common values and a civic culture*, (ii) *social order and social control*, (iii) *social solidarity and reduction in wealth disparities,* (iv) *social networks and social capital*, and (vi) *place attachment and identity* (p. 2129). The last one is of special interest here due to focusing on „…creating relationships between individuals, about empowering the individual as well as local communities" (Kearn and Forrest, 2000), and is assumed here as being covered by the measures of subjective community wellbeing. This aspect will be briefly explored with data from Social Diagnosis, a biannual survey of attitude and wellbeing on a large nation-wide representative sample.

As regards modeling of multilevel *relationships* **–** between ***individual*** and community wellbeing – two approaches are employed here (Okrasa, 2017). One is a between level *interaction*-focused approach concentrated on decomposition of variance into *within* group (differences among individuals in community, level – 1) and *between groups* (communes, level-2), *reflecting* differences across communities. To this aim, models for hierarchically structured data seem appropriate, which however are not free of a risk of 'ecological fallacy' (Goldstein, 2003(2010); Subramanian, 2009). In a parallel way, there is a 'causal' type of modeling checked as well. Specifically, we employ *structural* modeling of *(causal) mediation mechanism,* which consists of decomposition of total effect of the independent ('treatment') variable into the natural *direct* and *indirect* effects (Hong, 2015). Within this approach, community wellbeing can be hypothesized as a mediating factor between an objective (material) status of a person and her subjective wellbeing.

It was also hypothesized that in addition to the characteristics of a locality (place/commune) itself, spatial relations, proximity (distance) have impact not only on both the level of relevant measures – i.e., on both individual and community wellbeing – but also on the character of the relationship between them. Consequently, spatial (dependence) analysis is explicitly applied too. However, given the nature of the problem involving estimation of the impact of space on relation between variables rather than of their parameters we do not employ *spatial statistics* in version of *model-based* strategies, i.e. SAE/*Small Area Estimation* (Rao and Molina, 2015). Given also character of available data, a spatial *econometric* version of *data-exploration* was applied using *data-driven* strategies for analyzing patterns in geo-referenced data. Specifically, GeoDa (*Spatial Data Analysis* for non-GIS data, Anselin, 1995, 2005), and ESDA (*Exploratory Spatial Data Analysis*, Fischer and Getis, 2009) were used to this aim.

## Data and measures of wellbeing

In order to analyze individual (subjective) wellbeing and quality of the living environment, community wellbeing, a multi-source analytical database was constructed which contains data from *Time Use Survey* 2013 (TUS) and the *Local*

*Data Bank* (LDB), and data from *Social Diagnosis* 2013 (SD). The procedure for integrating the data sets in the multisource analytical database (MADb) was based on the geographical information, i.e. X,Y coordinates of the locations (gminas) from which the respondents were drawn to the respective surveys (TUS and Social Diagnosis). Initially, it was arbitrary decided that 20 persons is the minimum number of respondents needed to be identified in a gmina to have it included to the MADb[5]. But for some calculations 10 persons were also used.

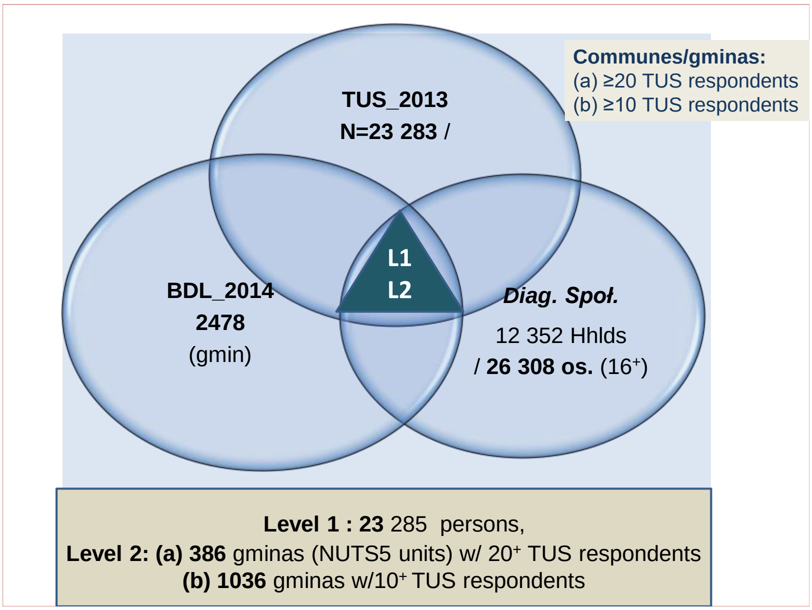



**Figure 1.** Multi-source analytical database: BDL & TUS (& DS). The NUTS5 unit's (commune's/gmina's) territorial KODTERYT was used as key merging code (X, Y– *coordinates)*

**Community wellbeing – *Multidimensional Index of Local Deprivation* (MILD)**

An objective measure of community wellbeing was applied to calculate the level of local deprivation of each of 2478 communes (gminas) using data from public file, Local Data Bank. The index – Multidimensional Index of Local Deprivation (MILD) – is composed of 11 domain-specific scales constructed by confirmatory Factor Analysis (each domain was pre-defined in a single-factor version of the FA, Okrasa 2013b[6]). The following domains of deprivation are

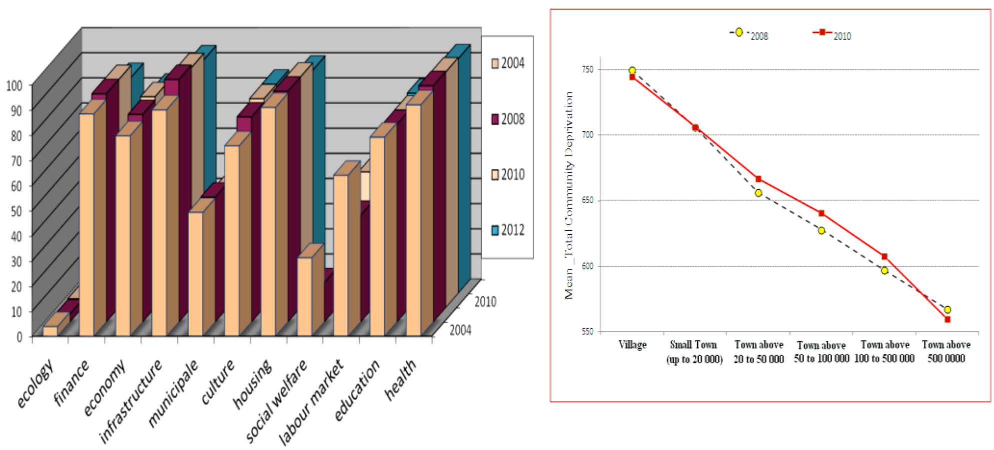
[5] The 20 persons cluster drops into interval 15-30 persons which is most often used in multilevel analysis under the rule of thumb, a rationale for which is that it satisfies the requirement of sufficient sparseness in defining a 'synthetic neighborhood' (Clarke and Wheaton 2007).

[6] The selection procedure consisted of: selection of domains – selection of indicators within each of the areas on the basis of factor analysis (principal component analysis) – standardization in the indicators – aggregation in the index for a given area – normalization of indicators for each area – composite aggregation in the global index (Okrasa 2013).

included: ecology, finance, economy, infrastructure, municipal utilities, culture, housing, social welfare, labor market, education, and health. Since Cronbach's alpha exceeded. 75, they were combined into as synthetic measure, MILD. As suggested by the term 'deprivation' all the component scales and composed of them MILD are of negative type measure (destimulants): the higher the index (scale) value the worse the community situation with respect to a given domain or to the total local deprivation (MILD). The values of MILD are strongly place dependent, decreasing sharply as moving from rural to urban areas, and along with the growing size of town – see Figure 2 a and b.

**Figure 2.** Multidimensional Index of Local Deprivation (MILD) by

(a) size of place of living (b) component scales over years 2004-2012




There was also a subjective community well being measure calculated using data from Social Diagnosis – on the basis of answers to questions about satisfaction from selected aspects of quality of life in a community: (1) locality (place), housing, and security (LHS); (2 social relations in family and in neighborhood, life achievements, and self-esteem (FSE); (3) life perspective while living ‘in here’, financial situation, and work possibilities (LPH). While regressed on the local deprivation (MILD), all these measures showed to negatively associated. It should be noted, however, that some items expressing community subjective wellbeing, such as 'sense of belongingness' or 'place attachment and identity'' and so on, are also present among the items constituting scales of community cohesion.

## Individual (subjective) wellbeing – the Time Use Survey data-based U-index

Following various definitions of individual (subjective) wellbeing there is variety of well advanced measures proposed in the literature. Nevertheless, there are still some doubts raised by psychometricians concerning validity of particular scales, while some statisticians and econometricians express reservations toward employing strong analytical tools to ordinal-level measurement data, as most of the scales is built up of the Likert-type items. Therefore, an alternative approach consisting of use of the time use survey data (usually collected with the day reconstruction method – Kahneman et al., op cit. 2004) met recently with growing interest. Especially, the TUS-based methodology developed (notably, due to Krueger et al., 2008) which combines objective information about the time respondent spent on performing activities with subjective rating of feeling associated with this performance. In the TUS conducted by the Central Statistical Office in 2013 three-point scale was used: 'positive' – 'neutral' – 'negative'. In accordance with the above methodology, U-index is defined as follows::

$$U_i = \Sigma_j \, I_{ij} h_{ij} / \Sigma_j h_{ij} \quad \text{(where I = -1 or 0 or +1)}$$

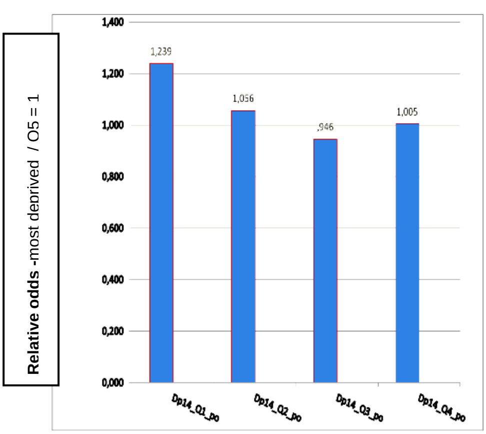
and $$U = \Sigma_i(\Sigma_j \, I_{ij} h_{ij} / \Sigma_j h_{ij}) / N \quad \text{for N-persons (in population)}$$

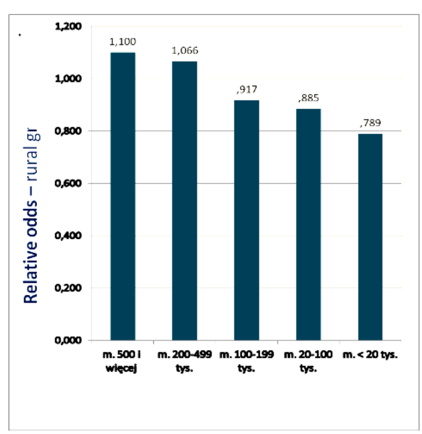
In calculation, it shown that the share of time spent for performing negatively rated activities was relatively low for most of the performed activities, hence to the U-index included were also 'neutral' cases – so, its interpretation should be rather as reflecting 'non-positive' than 'unpleasant state'.

At a glance, the relationship between objective CWB, as measured by MILD, and the U-index for all activities (excluding sleep) can be characterized by the relative odds of the U-index for MILD-quintiles of communes (gminas) – see Fig. 3, where the highest quintile, i.e. the 'most deprived' communes is set for the reference category. It suggests a tendency to generally bigger chance of being discontent due to spending relatively more time in 'non-positive state' among people living, on average, in more affluent communes (though the tendency is not strictly linear).

**Figure 3.** Odds of experiencing 'non-positive' feeling associated with activities, U - index, depending on

(a) the level of *local deprivation*/MILD (b) the size of the living place

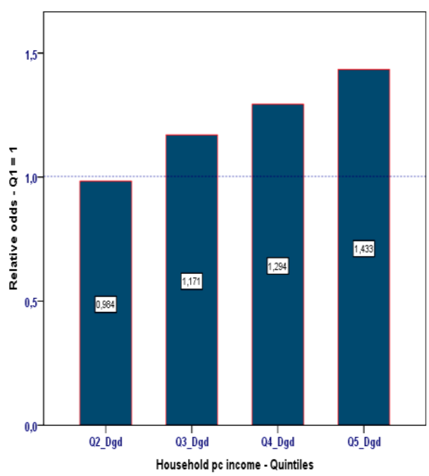


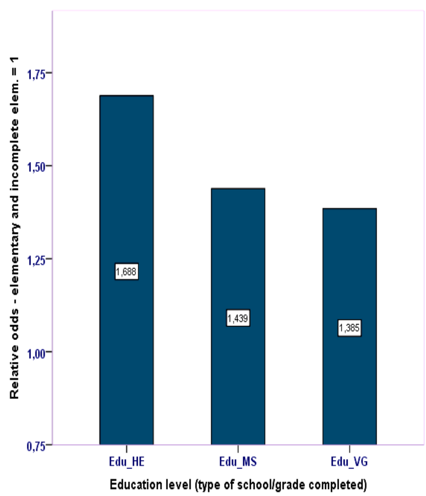
The negative pattern of tendencies – i.e. residents in more affluent urban environment (commune) are on average less satisfied with their life (in term of the U-index) than in less developed rural areas and small towns – should be interpreted with some caution due to the fact that they may perform different type of activities in different environments. For instance, shares of highly disliked activities associated with work or learning or house maintenance may be higher among city and big town dwellers, while shares of such activities like leisure time or social life or physical exercise or hobby and other performed on non-obligatory basis can be proportionally bigger among residents in small towns and rural areas. Validity of such observations can be supported indirectly by looking at some personal level characteristics which also are strongly related to the kind and size of the living place like income and education – Fig. 4, below.

**Figure 4.** Odds of experiencing 'non-positive' feeling associated with performed activities, U - index, depending on

(a) level of household pc income




(b) level of education




The emerging pattern of tendencies presented by the above figures suggests that behind a given level of local deprivation (i.e. MILD score, used here as the key indicator of CWB) operates a pretty consistent configuration of place-related factors: Urban (rather big) areas populated by on average better educated and wealthier people, who also seem to function in qualitatively different way (e.g. they are more likely to engage in activities which are generally less valued than those performed by dwellers in apparently less displeased rural areas and small town).

**Community deprivation, community cohesion, and individual wellbeing.** The following questions were asked in the analysis prior to multilevel modeling:

- Does the level of community deprivation /MILD affect the measures of community cohesion?

- Does the level of community cohesion influence the level of individual wellbeing (U-index)?
- How community deprivation and community cohesion affect jointly the individual wellbeing (U-index)?

Community cohesion – meant here synonymously with the Community Subjective Wellbeing (CSWB) – entails 3 scales calculated from the Social Diagnosis data and concerning satisfaction from three aspects of life in the community: 1. Locality, housing, security (LHS); (2. Social relations in family and in neighborhood, and life achievements (FSE) 3. Life perspective while living where s/he lives ('in here', LPH). Regressed on the local deprivation (MILD) all these measures remain with it, as it could be expected, in negative relation – Table1.

**Table 1.** Influence of the community level of (overall) deprivation (MILD_2014) on the measures of subjective of community wellbeing/CSWB

| Predictor: | 1. Locality etc/LHS | 2. Social relations /FSE | 3. Life perspective 'here' | 4. IWB/U-index (all activities) |
|---|---|---|---|---|
| Community deprivation/MILD_2014 | - 0.027** | -0.120** | -0.237** | -0.034** |

**) significant at $p < 0.01$

The relationships between the three datasets-based measures – CWB (in terms of local deprivation/MILD-2014), community cohesion (SD-based scales, used in Table 1 as measure of subjective-CWB), and individual wellbeing (U-index) were preliminary explored to determine the influence of the former two variables on the latter – results are in Table 2.

Each of the three measures of community cohesion (or subjective community wellbeing/S-CWB) – that was negatively associated with local deprivation (MILD-2014, in Table 2) – remains in also inverse relations with individual wellbeing. The U-index is consistently negatively affected by locality (place), housing, and security (LHS); by social relations in family and in neighborhood, (FSE), and by life perspective (LPH). However, the interaction effect, i.e. joint influence of such combination like, say, high gmina's deprivation and high level of satisfaction from own locality (gmina) is generally positive: higher (lower) satisfaction from their localities of the residents in better-off (worse-off) gminas reinforces the impact of the latter on lowering (increasing) the level of their displeasure (U-index).

**Table 2.** Regression of individual well-being – U-index – on *community deprivation* (MILD) *and community cohesion* (CSW-B)

| **Model** | **St. coeff** | **t** | **Signific** | | | |
|---|---|---|---|---|---|---|
| **Predictors:** | **Beta** | | | **df** | **F** | **Signif.** |
| **I** | | | | | | |
| (Constant) | | -1,530 | ,126 | 3<br>22368 | 16,180 | ,000 |
| Comm. deprivation/MILD_2014 | ,188 | 3,239 | ,001 | | | |
| FSE – Soc. relations, family and neighborhood, self-esteem | -,170 | -3,653 | ,000 | | | |
| Interaction MILD*FSE | ,304 | 3,893 | ,000 | | | |
| **II** | | | | | | |
| (Constant) | | ,379 | ,704 | 3<br>22368 | 15,972 | ,000 |
| Comm. deprivation/MILD_2014 | ,105 | 1,787 | ,074 | | | |
| PPH – Life perspective – ‘in here’ | -,118 | -2,694 | ,007 | | | |
| Interaction MILD*PPH | ,181 | 2,444 | ,015 | | | |
| **III** | | | | | | |
| (Constant) | | -1,530 | ,126 | 3<br>22368 | 13,607 | ,000 |
| Comm. deprivation/MILD_2014 | ,188 | 3,239 | ,001 | | | |
| LHS – Locality, housing, security | -,170 | -3,653 | ,000 | | | |
| Interaction MILD*LHS | ,304 | 3,893 | ,000 | | | |

## III. The cross-level interplay – issues in modeling

### Effect of interaction

Multilevel modeling of individual wellbeing and community wellbeing starts with **a b**asic structure of a model to deal with cross-level relationships, which should have the following elements and features (following Goldstein 2003, Subramanian 2010, and Okrasa 2017):

– $\boldsymbol{y_{ij}}$; wellbeing of *i* individual in *j* commune/gmina;

– $\boldsymbol{x_{1ij}}$ predictor of individual (level-1) – such as: income, age, education, or satisfaction (e.g. from life in a community, family life, etc.

– predictor of level-2/(macro-level) – CWB, here Multidimensional Index of Local Deprivation for j-gmina; $MILD_j$

Model for level-1: $y_{ij} = \beta_{0j} + \beta_l x_{1ij} + e_{0ij}$ (1)

where: $\beta_{0j}$ – refers to $x_{0ij}$ average score on a wellbeing scale in j-th commune /gmina; (e.g. 'less affluent' or 'more disadvantageous', etc.', < Me, $x_{0ij}$ =1);

$\beta_l$ – average differentiation of individual wellbeing associated with individual material status, ($x_{1ij}$), across all gminas;

$e_{0ij}$ – residual term for the level-1.

Treating $\beta_{0j}$ as random variable: ($\beta_{0j}$ – $\beta_0$) + $u_{0j}$, where $u_{0j}$ is locally-specific associated with average value of $\beta_0$) for a specified group (e.g. less satisfied from a community) and grouping them into fixed and random part components ($e_{0ij} + u_{0j}$) we obtain *variance component model,* or *random-intercept* model:

$$y_{ij} = \beta_0 + \beta_l x_{1ij} + (e_{0ij} + u_{0j}) \quad (2)$$

Modeling *fixed-effect* we include a level-2 predictor – MILD – (index of local deprivation) along with individual characteristics, including *interaction* term between the two levels *characteristics*

$$\beta_{0j} = \beta_0 + \alpha_1 MILD_{1j} + u_{0j} \quad (3)$$

$$\beta_{1j} = \beta_1 + \alpha_2 MILD_{1j} + u_{1j} \quad (4)$$

where $MILD_{1j}$ – context variable, predictor of differences between gminas.

Two-level model can be specified as below (following Subramanian, op cit., p. 520-21):

$$y_{ij} = \beta_0 + \beta_l x_{1ij} + \alpha_1 w_{1j} + \alpha_2 w_{1j} x_{1ij} + (u_{0j} + u_{1j} x_{1ij} + e_{1ij} x_{1ij} + e_{2ij} x_{2ij}) \quad (5)$$

where $w_{1j}$ is a 2-level predictor, i.e. the index of local deprivation, $MILD_{1j}$.

According to the above structure, $\boldsymbol{\alpha_1}$ provides an estimate of the (marginal) change in individual wellbeing (U-index) for a unit change in the level of gmina's deprivation for those below the median, or not in the 'unpleasant state'; while $\boldsymbol{\alpha_2}$ estimates the extent to which the marginal change in subjective wellbeing (U-index) for unit change in the gmina deprivation index (MILD) differs from that for those in the 'unpleasant state'.

Formally, such a specification of cross-level (between individual and community/gmina measures of wellbeing) *modification* or *interaction* effect should ensure robust estimation (e.g. Subramanian, op cit., p. 521, Hox et al., 2018). However, as already noted, the available data related limitations impose some restriction on the exactness of the employed calculation strategy. Therefore, the following model was calculated using data from Time Use Survey:

$$IWB(U\text{-}index)_{ij} = \beta_{00} + \beta_{10} education_{ij} + \beta_{20} age_{ij} + \alpha_1 MILD_j + \alpha_{11} education_{ij} * MILD_j$$

$$+ \alpha_{21} age_{ij} * MILD_j + u_{1j} education_{ij} + u_{2j} age + u_{0j} + e_{ij} \quad (6)$$

Preliminary results are in Table 3.

**Table 3.** Multilevel regression of individual wellbeing – *U-index* for all activities – on individual and commune/*gmina* level variables with cross-level interaction terms.

| Model: predictors | Weekdays | | Weekend /holiday | |
|---|---|---|---|---|
| | Beta | t | Beta | t |
| Constant | (.726)** | (6.316) | (.333)** | (3.515) |
| Education | -.085 | -1.136 | -.089 | -1.209 |
| Age | -.299** | -4.015 | -.008 | -.105 |
| Multidimensional Index of Local Deprivation /MILD_2014 | -.098* | -2.556 | -.046 | -1.209 |
| Education * MILD_2014 | .142* | 1.900 | .145* | 1.97 |
| Age * MILD_2014 | .115 | 1.497 | -.029 | -.383 |
| Urban (rural omitted) | .011 | 1.280 | .016* | 1.966 |
| | F (6.22698) = 174.860** | | F (6.24068) = 23.515** | |

Since the additional but crucially important focus was on spatial aspects of the relationships (interactions), the working strategy shown to be in practice spatial regression with both level variables included in the respective equations, as an explicitly interaction term. Neglecting for the time being this path of analysis, the next modeling issue concerns searching for a causal mediating mechanism.

## IV. Bringing *space* into the question

Estimation of the spatial regression model parameters (notation for individual observation *i*):

$$y_i = \rho \sum\nolimits^{n}_{j=1} W_{ij}\, y_j + \sum\nolimits^{k}_{r=1} X_{ir}\, \beta_r + \varepsilon_i \tag{7}$$

<u>where</u>: $y_i$ – the dependent variable for observation $i$; $X_{ir}$ $k$ – explanatory variables, r = 1, …, k with associated coefficient $\beta_r$; $\varepsilon_i$ is the disturbance term; $\rho$ is parameter of the strength of the average association between the dependent variable values for region/observations and the average of them for their neighbors (e.g. LeSage and Pace, 2010, p. 357)

The above specification of the spatial regression model assumes that $\varepsilon_i$ is meant as the *spatially lagged* term – versus *spatial error* formulation – for the dependent variable (which is correlated with the dependent variable), that is:

$$\varepsilon_i = \rho\, W_{i.} y_i + X_{i.}\, \beta + \epsilon_i \tag{8}$$

These two types of models allow us to examine the impact that one observation has on other, proximate observations. The results in Table 4, below, are for the spatial error model.

**Table 4.** Spatial dependence/spatial regression of SW-B (U-index) on commune's attributes and compositional characteristics

***SPATIAL ERROR MODEL*** **- MAXIMUM LIKELIHOOD ESTIMATION**

**Dependent Variable : *U –index* Number of Observations: 937; Mean dep var : 0.361195 Number of Variables : 8;**

**Degrees of Freedom : 929**

**Lag coeff. (Lambda) : 0.431769 ; R-squared : 0.123681**

| **Variable** | **Coefficient** | **Std.Error** | **z-value** | **Probability** |
|---|---|---|---|---|
| CONSTANT | 0.523731 | 0.042847 | 12.2233 | 0.00000 |
| MONTHLY INCOME | -0.002730 | 0.001960 | -1.40359 | 0.16044 |
| AGE_avg (%) | -0.014313 | 0.005653 | -2.53177 | 0.01135 * |
| EDUCATION_HS+ (%) | 0.000381 | 0.000222 | 1.71849 | 0.08571 * |
| NOT WORKING POP. (%) | -0.001304 | 0.000273 | -4.77623 | 0.00000 * |
| ILD_ECOLOGY | 0.000560 | 0.000462 | 1.21309 | 0.22510 |
| ILD_SOCIAL POLICY | -0.000415 | 0.000312 | -1.32693 | 0.18453 |
| SUBSIDIES_pc | 1.2323e-005 | 1.1588e-05 | 1.06344 | 0.28758 |
| LAMBDA | 0.431769 | 0.0677941 | 6.36883 | 0.00000 |

DIAGNOSTICS FOR HETEROSKEDASTICITY -- RANDOM COEFFICIENTS

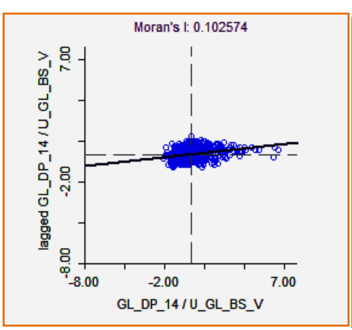
| TEST | DF | VALUE | PROB |
|---|---|---|---|
| Breusch-Pagan test | 7 | 54.7759 | 0.00000 |

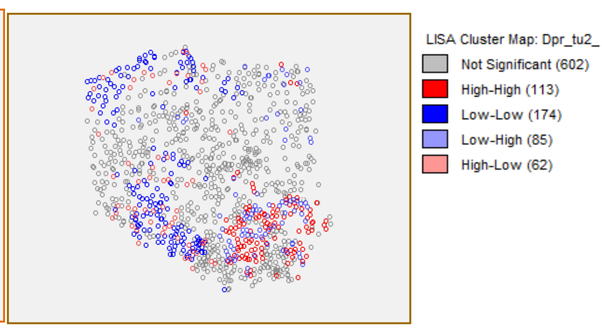
DIAGNOSTICS FOR SPATIAL DEPENDENCE -- SPATIAL ERROR DEPENDENCE

| TEST | DF | VALUE | PROB |
|---|---|---|---|
| Likelihood Ratio Test | 1 | 36.1346 | 0.00000 |

Few variables that represent commune's compositional characteristics (average percentage) influence significantly the individual (subjective) wellbeing in a negative way: age, education, population not in work is the factors operating in space dependent manner. Other two – monthly income and deprivation in the domain of social policy – which also affect residents' wellbeing negatively (though not in statistically significant way) indicate important direction of further exploration and of clarification from the development policy standpoint accounting for spatial aspects. Some illustration is given below, in Fig. 6 and 7, following presentation of the scatter plot and map jointly for subjective wellbeing (U-index) and local community deprivation (MILD), Fig. 5.

**Figure 5.** Individual SWB/*U-index* (all activities) and the level of commune (gmina) local deprivation/MILD$_{2014}$. Moran I = 0.103



Compared to earlier results concerning the relationship between community (deprivation) and subjective wellbeing (according to U-index) addition of spatial aspects to its exploration brings clarification with respect to the question of where there are low-low or high-high levels of its occurrence.

While checked in a separate way, the spatial association between some of the above variables and subjective wellbeing in a particular type of activity (U-index) indicate different direction. For instance, local deprivation in social policy and U-index for 'caring for children', below Fig. 6, or deprivation in local labor market and U-index for commuting (work and other 'target places'), Fig. 7.

**Figure 6.** U-index for caring for children by the level of local deprivation in social policy. Moran I= 0.18

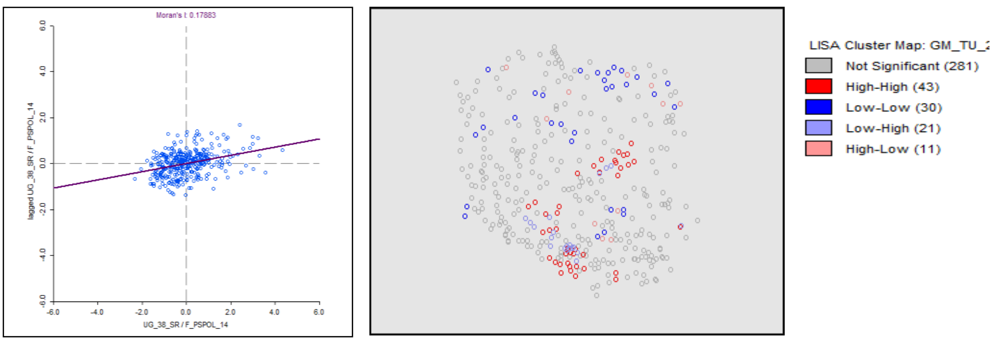
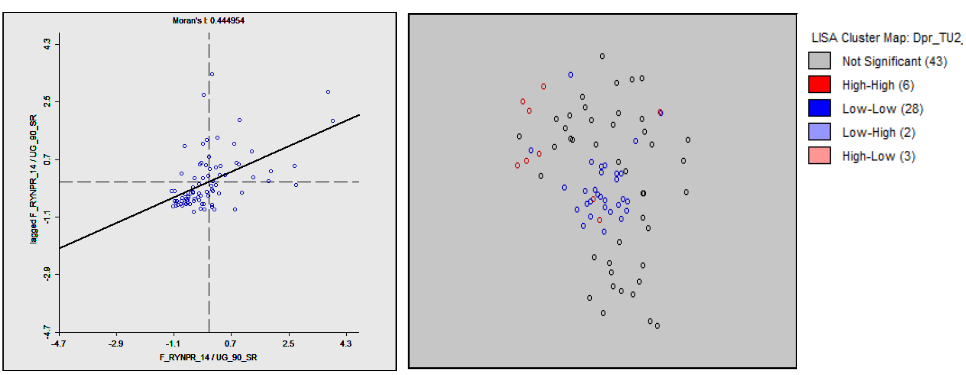



**Figure 7.** Individual wellbeing/U-index for commuting, i.e. associated with traveling to work and similar (target places or commuting), and gmina's (local) deprivation in the domain of local labor market (Masovian) Moran-I = 0.44)




Several conclusions can be drawn from the above patterns of spatially related association between quality of local environment (community constituting household's immediate surroundings) and subjective wellbeing, two of them are worthwhile to note here. First, more specifically defined relations – for concrete type of activities and of domains of local deprivation – can be analyzed in the multilevel spatial analytical perspective more effectively than using synthetic measures. Also, lower level of territorial cross-section values rather than countrywide global values is more appropriate in search for identification of spatially dependent phenomena and their interconnections.

## Conclusion

In view of the doubts and critique coming from experts of different disciplines - including psychometricians and econometricians – concerning the measurement of individual (subjective) wellbeing, the Time Use Survey data seem to provide a unique opportunity to explore relationships between individual and community wellbeing, using at the same time public statistics files created for other purposes.

In general, the level of dissatisfaction accompanying the performance of everyday activities – experiencing 'unpleasant state' and lower subjective wellbeing – increases along with greater household income. Paradoxically enough, individual wellbeing is diminishing (U-index grows) along with the lower level of commune's local deprivation. [In other words, overall conditions in less developed gminas constitute in general more favorable environment for individual (subjective) wellbeing – such aspects like social interaction, interpersonal relations might be of importance].

Community wellbeing reinforces significantly the subjective wellbeing effect of individual income. Since the influence of CWB on individual wellbeing is on average quite visible also in spatial terms – due to a tendency to cluster amongst gminas which are high-high or low-low on both dimensions – there is a need to analyze further such relationships, assuming availability of the appropriate data.

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