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MODELLING THE IMPACT OF COMMUNITY WELL-BEING ON INDIVIDUAL WELL-BEING. AN EMPIRICAL APPRAISAL OF ALTERNATIVE APPROACHES

Abstract

Measuring complex multidimensional phenomena such as the community well-being over time within a pragmatic approach focused on policy evaluation purposes provides several challenges for public statistics. The main difficulties are due to changes of well-being – at both group/community level and at the individual/household level – in terms of time – and space-related measures. The former is addressed here by employing an explicitly 'diachronic' approach through transforming original time-related data into Functional Data using Multivariate Functional Principal Component Analysis/MFPCA. The latter calls for accounting for heterogeneity of place–related impact of community on the individual (residence) well-being through employing multi-level modelling with cross-level operating factors – such as the level of community development/underdevelopment in terms of Multidimensional Index of Local Deprivation (MILD) and income or education level – in an alternative ways. One focuses on the estimation of cross-level interaction between persons' and community well-being; another looks for causality effect using a structural modeling approach. The role of spatial differentiation among the communities is checked directly through employing spatial statistics instruments – autocorrelation and spatial dependence – allowing also for identifying a tendency to clustering among the units of lowest territorial granulation (NUTS5 units/ LAU2 gminas) along with its geographic patterns.

Keywords: *subjective well-being, spatial analysis, multilevel modeling, functional data, measuring community well-being*

Introduction – problem and context

The main objective of this study is to explore modeling approaches to assess the strength and impact of the relationship (mutual influence) between community well-being and individual/household well-being based on public statistics datasets. While the latter is a challenge in itself – due to the lack of availability of a multi-source analytical database with a hierarchical (nested) data structure – the empirically demonstrated effectiveness of different, problem-specific approaches to analyzing the cross-level interaction effect becomes important both from a methodological and (local) development policy perspectives. Pragmatic reason to emphasis the relationships between community and individual well-being – reflects the growing demand for devices to better allocate the scare resources across communities (communes/ gminas) while accounting for individual (subjective) wellbeing. The complexity of the intertwining methodological and substantive issues involved in analyzing the relationship between individual and community well-being, taking into account both temporal and spatial aspects of cross-level dynamics, is addressed in two steps:

I. at the measurement level, the Functional Data measurement approach is employed in the version of *Multivariate Functional Principal Component Analysis* (MFPCA) to
II. deal with multidimensionality and temporality of community development (deprivation) and of individual (residents') subjective well-being.
III. having constructed a classification of both local communities (communes) and their inhabitants (for a given time period), a spatial perspective is employed – the spatial and place-based effects of community development on the resulting cross-categorization of units are assessed in terms of spatial patterns (autocorrelation and clustering tendency), spatial dependence, and spatial regression.

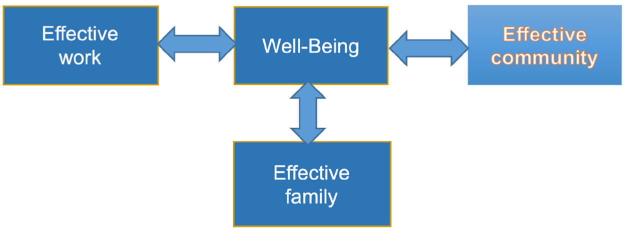
Conceptualization and operationalization of community well-being (CWB) in the evaluation policy research context

Two complementary outlooks appear relevant in such a context: (i) *methodological,* starting with an overview of the main approaches (paradigms) to measuring CWB in public statistics, and (ii) *analytical*, checking distributional potentials of the CWB indicators for geographic targeting of public resources, including their effects for reducing:

- local deprivation_(of g*minas*) and contributing to 'social progress' in the local context (*beyond GDP* as measures of social progress, OECD, 2015), and using dual type measures – objective and subjective – for the CWB (e.g., Kim and Ludwigs, 2017, Okrasa 2017).
- inequalities among 'localities' (*gminas*) with-implications for spatial cohesion and community cohesion (Okrasa 2017, Okrasa and Rozkrut 2018); and focusing on selected topic areas (out of five, as specified by Forrest and Kearns,2001): *reduction in wealth disparities,* and *place attachment and identity*

Key issues in analyzing the relationship between community and personal well-being: measurement – data – models A well-being measure is presumed to be generated not only to satisfy formal requirements but primarily to guide policy, especially about local community development (e.g., Alkire et al., 2015). Therefore, an adequate well-being measure must be understandable and easy to describe, and conform to 'common sense' notions of well-being, and be able to target the deprived, …, be technically solid and operationally viable, and be easily replicable (Székely 2006). All such recommendations are especially relevant in the context of pro-well-being community development. *Local Community* is meant here as any configuration of individuals, families, and groups whose values, characteristics, interests, geography, and/or social relations_unite them in some way (e.g., Dreher, 2016); in short, community is defined as the people living in a place such as a *neighborhood*.

Figure 1. *Well-being as an effect of interaction between its key factors: work – family – community*



Source: World Economic Forum, 2012. Global Agenda: Well-being and Global Success.

The fact that the key elements affecting personal well-being – work, family and community – also are influenced by the level of well-being, raises the question about what kind of measures ought to be used to describe it, and what types of relationships are included in an analytical model in order to assess them empirically

Methodological framework for analyzing Community WB and Personal WB. In order to analyze such entangled relationships, while accounting for the factors operating across individual and group (community) levels, a *multilevel modelling* approach can be considered and one of the two types of available strategies can be used. The first one embraces *decomposition of variance* into *within* groups/differences among individuals in a community (level – 1) and *between* groups (level-2) reflecting differences across communities; however, models for needed hierarchically structured data are exposed to risk of 'ecological fallacy' (Goldstein, 2003(2010); Subramanian, 2009; Sampson 2003). A way to avoid this can be to bring space into the question by employing *spatial (dependency)* analysis. *(ii)* Another approach is offered within s*tructural modelling* strategy focused on *(causal) mediation mechanism* – total effect of the independent variable ('treatment') can be decomposed into the (natural) *direct* and *indirect* effects (Hong, 2015; Morgan and Winship 2007; Okrasa 2017).

Table 1. *Type of tasks in measuring community wellbeing for policy research and evaluation*

Type of tasks in measuring community wellbeing for policy research and evaluation		
Interpetation of Community Wellbeing (CWB)	**Focus on monitoring and evaluation**	
	Changes in community relevant characteristics alone	Changes in both community and individual (residents') characteristics
- ***objective*** community wellbeing (CWB)	**A.One-level cross-section or dynamic**	**B. Multilevel w/cross-level effects**
- ***subjective*** communiy wellbeing (SCWB)	**C. One-level w/CWB as a 'context'** (subjective 'cohesion')	**D. Multilevel** with mutual influence and interaction

Source: Own elaboration: Opracowanie własne

Measures and Data

Measuring local deprivation and personal well-being

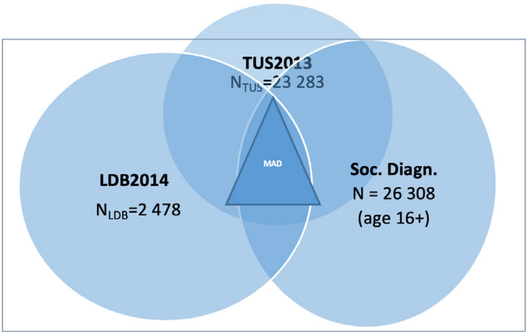
- *Multidimensional measures of well-being*, at both community and personal level. There are several reasons for focusing on community well-being in both research and policy considerations, especially in the local development context. Many of them have been recognized and discussed thoroughly in the literature, either as a part of the process or outcome of such development, challenging the tradition of using GDP and other economic indicators as measures of social progress (Phillips and Wong, 2017; Kim and Ludwigs, 2017; Lee et al., 2015).

However, efforts to go 'beyond GDP' in the evaluation of socio-economic progress were undertaken several decades ago – for instance, within the *social indicators* movement (see Land and Michalos, *Fifty Years After the Social Indicators Movement*, 2017). Methods of community well-being assessment, including subjective aspects of wellbeing, are becoming standard tools for policy purposes in several countries (Australia, Canada, USA and the UK). They all have one feature in common – they are based on self-reported assessment of selected aspects of well-being in connection with community, while community itself is in turn one of the components of the individual well-being measures. Community well-being is here represented by position of each commune (gmina) on the *Multidimensional Index of Local Deprivation (MILD)* that was constructed using *Confirmatory* Factor Analysis/PCA (single-factor was used) for each of 11 major domains of local deprivation. Each commune (gmina) was characterized by the value of combined loading factor (for 1st factor only) for selected on this basis original items in the following domains: *ecology – finance – economy – infrastructure – municipal utilities – culture – housing – social assistance – labour market–* education *– health;* altogether 67 items was selected out of several hundred, for years 2004, 2008, 2010, 2012, 2014, 2016 (for NUTS5 / LAU2, *gminas;* N; = 2 478); the MILD scale was set up to max 100.

- *Subjective Well-Being: individual and community subjective well-being*: Measurement of individual subjective wellbeing (SWB) was based on *Social Diagnosis*, a country-wide survey conducted every other year from 2003 to 2015. Also individual *quasi*-objective well-being was measured using *Time Use Survey* (one-off survey data). Community subjective well-being was measured with a compositional type of scale, based on self-reported satisfaction with selected aspects of life in *Social Diagnosis* survey.
- *Data.* The approach employed in the presented here analyses relies upon public statistics data being collected independently on different occasions, and integrated within the Multisource Analytical Database (MADb). This database is constructed through bottom-up procedure

using the territorial information – territorial code (KODTERYT) based on X, Y coordinates of each commune/gmina in the Local Data Bank/ LDB maintained by the Statistics Poland) – to identifying units (gminas) which also were surveyed in the relevant statistical research. Its core composition is presented in Fig. 2 as a triangle in the overlapping areas of three datasets: Local Data Bank = subsample of all gminas (2478), to which belong the individuals/households interviewed in either Time Use Survey (at least 15 persons per gmina) and/or in Social Diagnosis Survey (some of 26 308 persons of 16+ of age)

Figure 2. *Multiple-source Analytical Database / MADb containing bottom-up integrated data, with territorial code (KODTERYT) as an integrator*



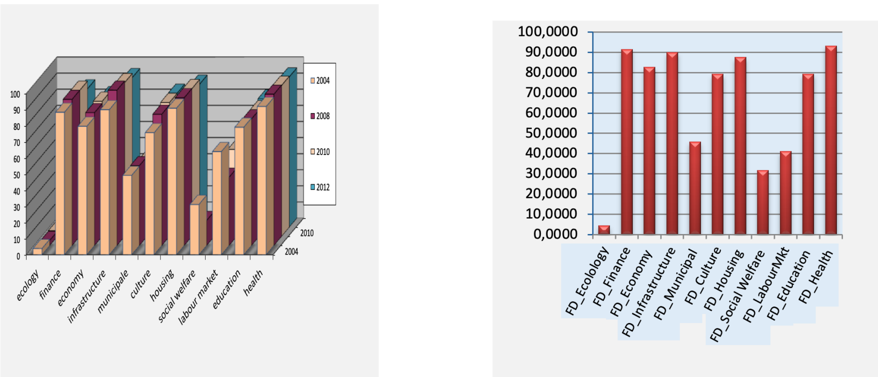
Source: Own elaboration.

A Functional Data approach. The fact that the major data needed for the measurement of well-being and analysis of the relationships between community and individual well-being were collected over the period from 2003/2004 to 2015/2016, makes it possible to adopt the 'diachronic' strategy that allows to use the information from each of the year covered by the subsequent observations in a cumulative way. To this *Functional Data* approach in the version of *Multivariate Functional Principal Component Analysis* (MFPCA) was used to deal with multidimensionality and temporality of community development/ deprivation and of individual (residents') subjective well-being, respectively.. The (MFPCA) is an extension of the classic principal component analysis PCA from vector data to functional data (Górecki, Krzyśko, Wołyński, 2019) with the procedure of representing data by function or curves. Of special interest here is an application to factorial methods allowing for combining the MFPCA with Cluster Analysis. The advantage of the FPCA over the classic PCA is to obtain a projection of analyzed units into one or two dimensional subspaces using information for the whole period under study, and to divide them into homogenous groups on the basis of the resulting rankings (Okrasa, Krzysko, Wpłynski, 2020). This difference can be illustrated by comparison of results of both types of data forms – according to the classic PCA and MFPCA –as in Fig. 3

Figure 3. *Comparison of local deprivation measures according to (a) classic PCA and (b) MFPCA (FD_deprivation)*

(a) Multidimensional Index of Local Deprivation /MILD – by domains (2004-08-10-14)

(b) Multidimensional Index of Local Deprivation /FD_MILD – by domains (2004-08-10-14)



Source: Okrasa and Gudaszewski (2017). Source: Okrasa, Krzysko, Wołynski (2020).

At a glance, the patterns of the component measures of MILD (i.e. for each domain of deprivation) for separate years, according to PCA, and of the measures by MFPCA, are very similar. To a large extent this is due to using FD-approach as a transformation of the PCA-based scales instead of the raw items from the Local Data Base.

Local community deprivation and community subjective well-being (CSWB) Three types of *measures of satisfaction* – as an indicator of the level of subjective well-being attributed to commune as a place of residents ('compositional' variable: percentage of 'satisfied' or 'very satisfied' on each scale) constitute the following separate scales: (i) satisfaction with *living condition*s – (ii) satisfaction with *living environment* – (iii) satisfaction with *social and family relations.* These scales are checked for relations in which they remain with the level of community deprivation in each of the domain. However a risk version of these scales was used instead of their original values to take into account not only the level of a domain deprivation but also a fraction of local community population as an assessment of 'probabillity' that such a specific type of deprivation will take a place; risk is defined as a product of probability and consequences ofa hazardous event' (like a commune's deprivation), according to the following formula (in logarithmic :

$$\text{Log RiskFD\_}_{\text{domain}} = \text{Log } [(\text{FD}_{d,} \text{ deprivation (in } \textit{d-domain}))] + \text{Log } [\text{P}_k \text{ x } (\text{ILD}_d \text{ / MILD})].$$

where:

– RiskFD_(domain) – risk in Functional Data version (in a given domain)

– ILD_d is the FD-scale of local deprivation in a domain d

– the respective fraction of the commune population (P_k) defined as the ratio of the ILD_d to the total size of local deprivation (FMILD

Results of the OLS simple regression of the (FD-scales) of subjective community well-being on the risk associated with each domain of deprivation are in Tabl. 2

Table 2. *Influence of local risk associated with particular domains of local deprivation on selected measures of satisfaction [N=386 communes /gminas]*

Pedictors OLS: Local Risk associated with domain of local deprivation as a single predictor	Functional Data Scales of Subjective Well-Being: *satisfaction with...*		
	All scales - synthetic measure of satisfaction	*Living conditions*	*Living environment*
FD_Risk assoc. w/ all domains	-.176 ** {-3.366)	-.100 * (-1.893)	-.107 **(-2.022)
FD_Risk assoc. w/ *ecology*	-.188 ** (-3.583)	-.098 * (-1.835)	-202 ** (-3.852)
FD_Risk assoc. w/ finance	-.194 ** (-3.7070)	-.119 ** (-2.249)	-.096 * -1.810)
FD_Risk assoc. w/ economy	-.201 ** (-3 .830)	-.123 ** (-2.311)	-.096 * (-1.812)
FD_Risk ass. w/ infrastructure	-.204 ** (-3.895)	-.123 ** (-2.327)	-.094 * (-1.760)
FD_Risk assoc. w/ culture	-.190 ** (-3.621)	-.112 ** (-2.105)	-.089 * (-1.679)
FD_Risk assoc. w/housing	-207 ** (-3.959)	-.119 ** (-2.236)	-.107 ** (-2.015)
FD_Risk ass. w/ soc.welfare policy	-.130 ** (-2.452)	-	-
FD_Risk assoc. w/ labor market	-.135 ** (-2.554)	-	-102 ** (-1.912)
FD_Risk assoc. w/ education	-.105 ** (-1.975)	-	-.125 ** {-2.349)
FD_Risk assoc. w/ health	-203 ** (-3.888)	-.123 ** (-2.310)	-.089 * (-1.677)

Source: Okrasa et al., 2020.

Significant negative values of the beta coefficient for the risk associated with MILD and with every domain of local deprivation (under-development) – especially with the domains of economy, infrastructure and health; also in ecology (for satisfaction with *living environment)* – confirm hypothetical expectations that the 'objective' community well-being, according to MILD and its components, impacts subjective aspects of residents' well-being (SCWB).

- *Local community deprivation and individual subjective well-being (PSWB)*. In order to check the above stated type of hypothesis in reference to the individual (community residents') well-being, the PSWB measures are built upon the *Time Use Survey* data. Survey research was conducted by Statistics Poland (TUS-2013) using *day reconstruction method*/DRM ,on a large nation-wide sample (N=23 000). To analysis was taken a subsample of communes (gminas) with at least 10 or more residents were surveyed as respondents of the TUS-2013. The well-being indicator was constructed as an econometric and psychometric combined approaches (Krueger and Khaneman et al.. (2008), defined on the basis of emotion (negative or positive) reported by respondent as his/her feeling associated with a performed activity – it means that *time of unpleasant state* was used as **U**-index:

$$\mathbf{U_i} = \Sigma_j \boldsymbol{I_{ij} h_{ij}} / \Sigma_j \boldsymbol{h_{ij}} \quad (\mathrm{TUS}_{2013}\text{: I} = -1; 0; +1)$$

and $\mathbf{U} = \boldsymbol{\Sigma_i(\Sigma_j\, I_{ij}\, h_{ij} / \Sigma_j\, h_{ij}) / N}$ for N-persons / group in population;

For U-binary (-1 & 0 vs. +1), odds of U [chance of other than 'pleasant' or non-positive state vs. 'pleasant'] is defined as proportion: $\mathbf{U_i / (1 - U_i)}$ **.**

According to the above interpretation of individual well-being as the proportion of time spent in 'unpleasant state' (doing something, either voluntary or not) odds U_i can be regressed on the community level FD-measures of (inverse) deprivation (development) and on its selected characteristics, as in Tab. 3

Table 3. *Effect of local deprivation and risk associated with local deprivation, and of selected local community characteristics for Individual subjective (quasi-objective) well-being measured with Time Use Survey dataset, in odds version (U_i/1-U_i)*

Model	Unstandardized Coefficients		Stand. Coeff.	t	Sig.
	B	Std. Error	Beta		
(Constant)	0,494	0,209		2,364	0,018
FD_Local (inverse) deprivation (2004-16)	0,000	0,000	-0,092	-2,204	0,028
Risk associated w/local labor market deprivation	-0,073	0,021	-0,211	-3,542	0,000
Risk assoc. w/depriv. of local economy	0,080	0,027	0,214	2,987	0,003
Temporarily absent (from home/1000 os.)	0,004	0,002	0,071	1,979	0,048
Proportion of 'employed' to 'not-employed' in comm.	-0,054	0,010	-0,175	-5,631	0,000
Number of NGOs per 1000 pers	-0,017	0,011	-0,049	-1,534	0,125
Local authority active in revitalization	0,069	0,026	0,085	2,715	0,007
F (7, 1012) = 9,7 842; p<0.001					

Source*:* Okrasa and Rozkrut (2018).

Almost all predictors (except for the 'number of NGOs per 1000 pers') have significant impact on subjective well-being (or rather quasi-objective, given that the time reported by respondent is less arbitrary as an indicator of it than a verbal assessment of 'satisfaction with' any aspect of well-being). However, the effect of the included predictors is mixed – negative sign of the beta coefficient indicates positive impact of a predictor, as it may be illustrated by the local deprivation (in functional data version), suggesting that prevalence of development (or reduction in deprivation) of a commune/gmina during the years under study (2004-2016) contributes to the decreasing level of residents' dissatisfaction (U-index). Similar influence show risk associated with local labor market and the proportion of 'persons employed' to 'not-employed' in a commune, while risk associated with deprivation in local economy and active involvement of local authority in commune's revitalization programs contribute rather to lowering chance for increased community well-being. It is worth noting that the mixed pattern of influence shown in Tab. 3 embraces predictors (characteristics) at the commune level.

Assessing cross-level interaction between personal (subjective) and community well-being

Having preliminary confirmed the existence of a significant (negative) relationship between community well-being indicators and the (subjective) well-being of individual residents, the question of assessing its strength leads to a comparison of the relative effectiveness of the two approaches discussed here – one based on principal component analysis in the functional data version (FDMPCA), other on its classical version (PCA). Given the two-level data analyzed, multivariate modeling seems to be the appropriate approach to test the above relationship.

- A basic *multilevel model* to be operationalized in terms of the analyzed here variables involves the following:
- $y_{ij;}$ well-being of *i* individual in *j*th commune/gmina;
- x_{1ij} predictors of the level-1 (persons) – such as: income, age, education, or satisfaction (e.g., with life in a community, family life , etc.
- predictors of the level-2 (group/community): *Multideminsonal Index of Local Deprivation* for *j*th commune (gmina) /$MILD_j$

Model for level-1 can be defined as below (e.g., Subramanian. 2010):

$$y_{ij} = \beta_{0j} + \beta_1 x_{1ij} + e_{0ij}$$

where: β_{0j} refers to x_{0ij} average score on a well-being scale in j-th commune/ gmina (eg., . 'less affluent' or 'low-income', < Me, x_{0ij} =1);

β_1 – average differentiation of individual well-being associated with individual material status , (x_{1ij}), across all communes; e_{0ij} – residual term for the level-1.

Treating β_{0j} as random variable: (β_{0j} – β_0) + u_{0j}, where u_{0j} is locally-specific associated with average value of β_0) for a specified group (eg. less satisfied with a community) and grouping them into fixed and random components ($e_{0ij} + u_{0j}$) we obtain *variance component model* or *random-intercept* model:

$$y_{ij} = \beta_0 + \beta_1 x_{1ij} + (e_{0ij} + u_{0j})$$

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 *:*

$$\beta_{0j} = \beta_0 + \alpha_1 MILD_{1j} + u_{0j} \text{ and } \beta_{1j} = \beta_1 + \alpha_2 MILD_{1j} + u_{1j}$$

Accordingly, a two-level model can be specified as below:

$$y_{ij} = \beta_0 + \beta_1 x_{1ij} + \alpha_1 w_{1j} + \alpha_2 w_{1j} x_{1ij} + (u_{0j} + u_{1j} x_{1ij} + e_{1ij} x_{1ij} + e_{2ij} x_{2ij})$$

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

The following model was calculated using data from *Time Use Survey* for personal well-being as dependent variable:

$$PWB(U\text{-}index)_{ij} = \boldsymbol{\beta}_{00} + \boldsymbol{\beta}_{10} education_{ij} + \boldsymbol{\beta}_{20} income_{ij} + \boldsymbol{\alpha}_1 MILD_j + \boldsymbol{\alpha}_{11} education_{ij} * MILD_j + \boldsymbol{\alpha}_{21} income_{ij} * MILD_j + u_{1j} education_{ij} + u_{2j} income + u_{0j} + e_{ij}$$

Such a specification of cross-level (between individual and community/ gmina measures of well-being) with i*nteraction* effect should ensure robust estimations (e.g.. Subramanian. op. cit.. p. 521; Hox et al.. 2018), they are shown in Tab. 4.

Table 4. *Multilevel regression of personal well-being – U-index (all activities) – on individual and commune characteristics with cross-level interaction term; comparison of Functional Data-based and classic PCA approaches*

Model FDPCA predictors	Std Beta	t	Model Classic PCA predictors	Std Beta	t
Constant		13,258	Constant		5,096
Income	0,056**	6,901	Income_rev_mean	0,027**	4,050
Education (years of schooling)	0,075**	4,728	Years of Education	-0,045	-0,610
FD_Community Development 2004-2014	0,082*	2,304	Community Deprivation 2004-2014	-0,062*	-2,133
FD_Education * Community Development	-0,111**	-2,737	Education * Community Development	0,123*	1,668
FD_Comm. Dvpt * Income	0,152**	17,778	Comm. Deprivation* Income	0,091**	13,547
F(5,15086) =100 418 (p<.001)			F(5,22690) = 87 196 (p <.001)		

Source: Okrasa et al., (2020).

There is strong similarity of the results obtained with FDPCA and PCA approaches, respectively. However, a more clear pattern of dependencies emerges in the first case, confirming the (expected) advantage of the FD-version of data as a better way of utilizing multidimensional and temporal information. Also, the overall pattern of empirical relationships becomes clearer when using the FD-version of PCA. Including the cross-level interaction term – community development (inverse of the community deprivation) and the residents' income *versus* community deprivation (inverse of the community development) and the residents' income.

- ***Structural modelling approach*** *with causal mediating mechanisms*: Local deprivation is assumed to play a role of a factor modifying effect of a commune's attribute on the residents well-being, according to U-index. The relevant hypothesis states that the level of deprivation of a commune (gmina) affects the way in which the residents' subjective well-being is being influenced by their material status (income). A structural modeling approach seems an adequate for verifying such a hypothesis (e.g. G. Hong. 2015)], using the following notations:
  Y – individual well-being – *U-index*
  Z – source of influence: HH income (average in a commune/gmina)
  M – *mediator*: level of local deprivation /MILD (or $ILD_{1,\ldots,11}$)

$$M = \gamma_0 + aZ + \varepsilon_M$$

$$Y = \beta_0 + bM + cZ + \varepsilon_M$$

Substituting for M, a *reduced-form* model is obtained:

$$Y = (\ldots) = \beta'_0 + c' Z + \varepsilon'_Y$$

Estimation of differences between coefficients of influence, c' – c, (with local deprivation, MILD as a mediator, allows to assess indirect effect (of MILD) in estimating influence of Hhld income on individual well-being (U). Such specification was made for selected domains of the local deprivation: economy – social assistance – labor market –and health – which showed clear and significant association with the material status of a commune's residents. Tab. 5 contains detailed results.

Table 5. *A structural (causal-type) modelling: the impact of the selected domains of local deprivation – as a moderating factor – in the assessment of influence of respondents' income on their subjective well-being*

Model / predictors	Standardized	Coefficients	Differences
	Beta	t	[c' – c
Dependent Var: U-index for all activities			
M I: *ILD_economy*	-.054	-1.565	0.286
Monthly income/ Mi (c')	.072 *	2.070	
ILD_economy on Mi (c)	-.358 **	-11.807	
M II: *ILD_social assistance*	-.091 **	-2.824	0.007
Monthly income /Mi (c')	-.111 **	-3.439	
ILD_soc asst. on Mi (c)	-.104 **	-3.214	
M III: *ILD_labor market*	-.089 **	-2.725	0.090
Monthly income /Mi (c')	-.061 *	-1.850	
ILD_labor market on Mi (c)	-.154 **	-4.802	
M IV: *ILD_health*	.054	1.638	0.108
Monthly income /Mi (c')	-.070 *	-2.137	
ILD_health on Mi (c)	-.178 **	-5.583	

Source: Okrasa (2018).

The impact of respondents' income on theirs (subjective) well-being is significantly modified by the level of local deprivation in selected domains (ILD); health and economy are relatively stronger factors than labor market and social assistance (but the latter are more important in the spatial context – see below).

Spatial aspects of cross-level relationship – accounting for spatial heterogeneity

Two types of issues arise as a consequence of recognizing that differences between communes (gminas, jako as places of living), affect the individual and group (community)/cross-level well-being relationships. They are (i) spatial similarity (vs. dissimilarity) of the included communes/gminas, in the relevant characteristics – this is an issue of potential autocorrelation and a tendency to geographic clustering with respect to selected terms; and (ii) spatial dependence, i.e., the question of determinants of the space/place-related determinants of the residents' subjective well-being. To this aim, the following research tasks are being undertaken:

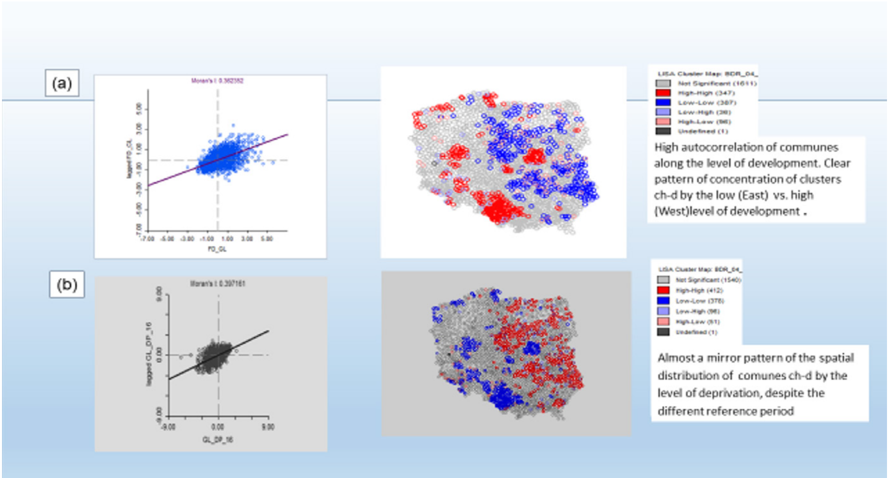
- spatial autocorrelation and the tendency to geographic proximity of selected measures of subjective well-being along with FD_deprivation (or development) in selected domains;
- spatial dependence of selected measures of subjective well-being – *spatial error model* of spatial regression on *FD_Risk* in the *labor market* and in the *local economy*, given a set of auxiliary covariates.

Autocorrelation. The first task calls for checking a tendency to clustering among 'spatial units' (communes/gminas) with respect to selected measures – subjective and objective – using Moran' I (global) coefficient of autocorrelation:

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

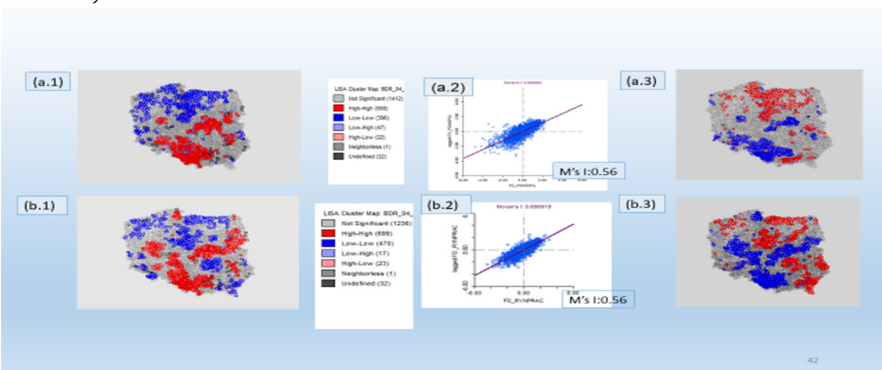
where: x_i, x_j – values of a measure at each location; $\boldsymbol{W}$ is the spatial weights matrix.

Figure 4. *Scatter plots and cluster maps of local deprivation according to: (a) FD_MILD$_{2004\text{-}2016}$ (M's I: 0.36); and (b) MILD$_{2016}$ (M's i: 0.39) – comparison (LISA – program)*



Source: Own elaboration.

Figure 5. *Cluster maps and scatter plots of deprivation / 'development' in the domains of (a) local social welfare by FD-measure (2004-16) and FA-classic and (b) local labour market by FD-measure and FA*



Source: Own elaboration.

Strong autocorrelation and clear pattern of spatial clusters in each of the two domains – local social welfare and labour market – provide case for interpretation of the above relationships between risk associated with FDPCA-measure and 'classic' PCA measure, (a.1&a.3, and b1&b.3, respectively): the patterns are similar (but inverted values suggests different interpetation – 'development' ('1') vs. deprivation ('3').

Spatial dependence (of selected measures) . Estimation of the spatial regression model parameters of the equation below (notation for individual/ commune observation *i*):

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

where: y_i – the dependent variable for observation i; $X_{ir}\, k$ – explanatory variables r = 1. …. k with associated coefficient β_r ; ***W*** matrix; ρ is parameter of the strength of the average association between the dependent variable for region/observations and the average of them for their neighbours; ε_i is the disturbance term – it might be assumed that ε_i is meant as either the *spatially lagged* term or *spatial error* formulation (eg.. LeSage and Pace. 2010).

Table 6. *Spatial dependence – spatial error model*
Dependent — Subjective well-being – (FD-measures) All scales – SMS/Synthetic Measure of Satisfaction (N 352)

Variable	Coefficient	Std.Error	z-value	Probability
CONSTANT	6.58928	4.69413	1.40373	0.16040
RiskFD_LabMkt	1.05379	0.470991	**2.2374**	**0.02526**
RiskFD_Economy	-1.4603	0.542753	**-2.69055**	**0.00713**
Subsidies FD_2016pc	0.000735	0.001080	0.68092	0.49592
NGOs per 1000_2016	-0.46272	0.2308	**-2.00488**	**0.04498**
Comm. w/revitalization	0.18080	0.381625	0.473771	0.63566
Migration_balance	0.04184	0.041461	1.00924	0.31286
LAMBDA	**0.16678**	0.0560501	2.97569	0.00292

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TEST	DF	VALUE	PROB
Breusch-Pagan test	6	36.8021	0.00000

SPATIAL ERROR DEPENDENCE FOR WEIGHT MATRIX : BDR_04_16_Juneo5_2019

TEST	DF	VALUE	PROB
Likelihood Ratio Test	1	8.4296	0.00369

Źródło *Source:*: Okrasa and Rozkrut (20252024).

In addition to risk associated with deprivation in the local labor market and local economy also presence of NGOs organizations in the local community contribute significantly to the level of satisfaction with several aspects of life (i.e., in terms of the synthetic measure of subjective well-being). Although a few predictors affect significantly the subjective well-being, the coefficient of Lamabda indicates that the relatively simple spatial error model fits to the data.

Conclusions

Following the conceptualization of the triadic interdependence of data, measurement, and model, some observations seem worth mentioning in light of the above presented empirical results. Bottom-up, data-driven approach to constructing Analytical Data Base encompassing individual and group/commune variables, seems to provide an alternative to the lacking appropriate (nested) data structure in analyzing cross-level relationship between the respective (development and well-being) measures, within a multidimensional framework. Functional Data approach to multidimensional measurement of community well-being (i.e., switching from PCA to FPCA), as well as to selected measures of subjective well-being, allows on the one side, to utilize information on long-term process of local development and, on the other, to expand the analysis towards employing a spatio-temporal framework, while clarifying the between individual (micro) and commune (macro) level relationships.

In summary, by taking into account the dynamic aspect of the local development process (by applying the Functional Data approach) in the analysis of its impact on the personal well-being of residents, both planning and resource allocation policies become better informed and, one might expect, more effective (for example, a given level of individual well-being can be achieved by using a more accurate policy-relevant information than otherwise, even at a higher cost, while neglecting it).

To provide a more complete picture of the complex relationships along with the factors influencing them, further research would be needed. This should involve (firstly) decomposition of the FD version (functional data) of local development (municipality) over the period under study (2004-16) into trajectory profiles constructed in terms of differences between values of the local measure of deprivation (like MILD) for subsequent time points of pairs of observations (2004-2008; 2008-2010; 2010-2012; 2012-2014; and 2014-2016), and (secondly) checking the impact of the type of municipality-specific trajectory (scaled from *systematic increase* to *systematic decrease* in community well-being) on the measure of individual well-being of its residents. A preliminary spatial examination of this hypothesis (Okrasa, 2026) found that well-being of the residents of municipalities with a positive trajectory (predominantly increasing community well-being, i.e., reducing local deprivation) generally showed to be influenced by factors such as municipal (gmina's) expenditures on education (school and preschool) or the municipality's *own income* (per capita), along with a tendency towards spatial autocorrelation (e.g., Moreno's I value – 0.118 and – 0.102). On the other hand, net migration within the municipality, which is also significantly and negatively associated with negative trajectory of deprivation – clearly affects the above pro-well-being factors (I = 0.173 and 0.222, respectively). However, the relationship between community-level deprivation and residents' subjective well-being proved more complex. In summary, these observations only call for deeper research insights into such analytically compelling and policy-relevant issue.

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