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Convergence or Divergence? Analysis of Regional Development Convergence in Hungary***

Abstract

The enlargement of the European Union (EU) led to an increase in regional development differences, challenging the EU structural policy. Whilst there are numerous papers discussing international and cross-EU development convergence, the issue seems under-researched at national level, especially when small territorial units are considered. This paper aims to partially fill this gap by using low aggregation (Local Administrative Unit 1, LAU1) territorial data between 2002 and 2013 - a period that comprises Hungary's EU accession and also the years of the recent Global Financial Crisis. We employ a novel approach to circumvent the lack of income, productivity or competitiveness data at LAU1 level by deriving two Regional Development Indices (RDI) resting on the estimation of internal migration functions. Once the RDIs are estimated, we proceed to a test sigma, beta and unit root convergence. Our results point towards regional divergence with rather bleak consequences for Hungarian and indeed European cohesion aims.

Keywords: Regional Development Indicator, Hungary, Sigma, Beta Convergence

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Introduction and literature review

European Union (EU) regions are characterised by considerable differences in terms of economic development and well-being. The enlargement of the EU led to an increase in these regional differences, challenging the EU structural policy. The goal of this policy is to strengthen economic, social and territorial cohesion by reducing the disparity in the level of development among regions and Member States (aiming to diminish 'disparities between the levels of development of various regions. and the backwardness of the less-favoured regions'; see Articles 130(f)–130(p), Single European Act 1987). To achieve this, structural programmes and funds have been established to promote the political objectives of convergence, regional competitiveness and employment, as well as European territorial integration. However, the distribution of regional and rural funds has been criticised as being ineffective and inefficient. Whilst researchers' and policy analysts' focus mostly rests on aspects regional disparities within the EU at higher aggregation levels (usually NUTS 2), they seem to miss assessing the regional convergence situation at sub-nation level, that is actually underpinning cross-European regional convergence. This paper aims to partially fill this gap, by using Hungarian low aggregation territorial data between 2002–2013 - a period that covers Hungary's EU accession and also the recent financial crisis period – and testing Hungarian regional convergence at LAU1 (formerly NUTS4) level.

Historical background

In Central and Eastern European Countries (CEEC), the transformation of political and economic systems in the 1990s, generally induced similar impacts with respect to the spatial inequalities of these countries' regions. With the collapse of socialism, the strong interlocking of industry and regional development halted, and, with the arrival of transition to western type market economy, localities entered the competition for resources. Consequently, out of competing regions, the new economic actors evidently choose their premises purely based on economic variables, leading to the development of new inequalities. The regional reorganisation and redistribution of wealth followed. Better endowed regions started to amass more important economic organisations, changing the spatial pattern of the CEEC's national economics (Beluszky & Győri 1999). Henceforth, the development of individual regions was at the mercy of market economy rules, negative impacts hitting the less favoured regions being at best mitigated by support through central Government redistribution and/or normative payments. Further, the un-competitiveness of regions previously mostly producing for Comecon[1] markets, coupled with the prolonged and uneven structural changes, led to even more pronounced within nation regional divergence. Most prominent symptoms of regional inequalities in the post-communist countries are the level of urbanisation and the extent of rural spaces, but there are significant differences between CEECs on this respect. Aside from Poland, where the urban population is still increasing, the outmigration from rural to urban areas has halted. More, in a number of countries (Kovács 2009) the within country migration turned, with the unemployed urban population moving to rural regions. Before transition, the rural areas and traditionally industrial suburbs had the highest percentage of active population. Opposite trends were observed in the larger cities. In every CEEC capital city, the population average age increased, predominantly due to growth of retired population's share (Kovács 2002).

Spatial differences of labour markets are mostly due to a re-structuring of economic systems. High employment rates were rather specific to regions where structural changes did not yet affect all branches of the economy, i.e. old structures persisted. In addition, there are regions where the quick development of previously neglected tertiary sectors could offset the shrinkage of the other branches of national economy. A particular paradox of CEEC transition is that successful regions displayed the lowest activity rates (Horváth 2004).

Certainly, the transition was a very country specific process. In Hungary, for example, the un-competitive socialist plants were closed or privatised (often at all costs), whilst Poles rejected the shock therapy and continued the operation of loss-making production plants for employment and regional policy reasons, whilst gradually improving their efficiency. The above partly explains why Poland was less exposed to the economic downturn of

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[1] Council for Mutual Economic Assistance. the economic organization of Socialist countries.

2008 than, for instance, Hungary (Faragó 2016). By the end of the 1990s, Hungary was beyond the transition crises of regional economies and on a growth track, whilst Poland. the Czech Republic and Slovakia – mainly due to the overstretched privatisation process and the continuous budget support of large production plants - were still ahead of the great structural and regional transformation process (Horváth 2004). Due to the lack of nationally available capital, in Hungary, the market economy mostly favoured international companies (Faragó 2016).

Similarly to other European countries, regions specialised in heavy and extractive industries were the losers of the transition process alongside – and this is a CEEC specificity – the large agrarian regions. This partly explains why amongst CEECs, Hungary presents one of the largest development differences at NUTS2 level. The picture is actually worse when NUTS3 decomposition is considered (Horváth 2004).

There was a general expectation in CEEC block that through the Community's regional policy the EU membership will bring a rather quick catching up with the Western European living standards. In many cases, however, these were false expectations. Some of the literature (Balogh 2012) argues that contra-productive subsides are to blame, whilst others (Jeney and Varga 2016) emphasise the growth of within nation regional polarisation to explain the lack of regional development convergence. The latter argument goes by saying that within the poorly developed regions only those can successfully absorb support, where there already exists sufficient material and human capital available – needed to efficiently use support. It follows, that only regions with better social economic status could benefit, thus increasing the within periphery polarisation.

Regional development indicator

Since the variables usually employed for convergence analyses (such as GDP – usually approximated with income) are not available at this disaggregation level, composing a synthetic indicator is mandatory. Regional convergence analysis requires the most realistic mapping of social-economic territorial inequalities, theoretically requiring the lowest aggregation possible of locality units. But considering the rather particular Hungarian settlement structure (high number of very small villages in addition to the disproportionate aspects found in spatially extended settlements of the

Alföld region), a regional development impact analysis seems to be best served by LAU1 (formerly NUTS4) aggregation.

Two broad research methodology categories with respect to complex indicators may be distinguished in the empirical literature. One stream (e.g. Csatári 1999; Hahn 2004; Faluvégi and Tipold 2007; Jeney and Varga 2016) of studies categorises the variables used for analysis into dimensions, and creates a composite indicator per dimension. Other papers (Fazekas 1997; Bíró and Molnár 2004; Faluvégi 2004; Obádovics 2004; Cserháti et al. 2005; Lukovics 2008; Ritter 2008; Lukovics and Kovács 2011; Bodnár 2016; Michalek and Zarnekow 2012) use all the available data as one group, arguing that value creating properties of the economy, human endowments, infrastructure, etc. are not independent manifestations but in strong interaction with each other. In the latter case, factor or principal component analysis allows the joint effect of variables that otherwise would be categorised into different dimensions. This is the approach we also favour in this paper. However, it does come with a caveat. Namely, the results of factor analysis are different to interpret – providing that individual factors need to be interpreted.

Convergence analysis

Convergence analysis originates from the neo-classical growth theories (see the seminal papers of Barro and Sala-i-Martin 1991, 2004; Dolado et al. 1994; Cuadrado et al. 1998; Coudrado-Roura 2001 for example). Newer theories treat factors such as human endowment or technological change responsible for long-run convergence as endogenous, giving birth to endogenous growth and new endogenous growth theories (see for instance Martin and Sunley 1998 for an excellent review). New economic geography roots in the endogenous growth theory but opens new possibilities by allowing the incorporation of spatial data in the models (see for instance Krugman 1998). Further, newer empirical models differentiate between regions, by allowing club clustering before testing for convergence. The matter of global and indeed regional convergence still heats up debates; it seems results are largely dependent on the time span, territorial unit and methodology employed. A number of papers focused their attention on CEEC countries (e.g. Wagner and Hlouskova 2002, Ferreira 2010), here as well, results vary, yet most papers found some convergence in the transition period of the 1990s. However, to the best of our knowledge, none of the papers focused on small regional building blocks (below NUTS2 or even NUTS3 level).

Thus, our research question is simple. Is there, especially in the light of EU membership and thus access to the Community's development funds, a convergence process amongst Hungarian sub-regions? Is the gap between the developed Central and North-Western regions and the agrarian South-East or formerly heavily industrialised North-Eastern regions closing? The rest of this paper is organised as follows. In the next section, we present the methodology, followed by the short description of the database we use. Section four is dedicated to the empirical analysis, and the final section concludes the research.

Methodology

Factor analysis

We utilise principal component (PCA) and factor analysis to reduce the number of variables describing the objective life conditions in sub-regions. We first test the data for the suitability of PCA using Kaiser-Meyer-Olkin measure and Bartlett's test of variable's independence, followed by rotation algorithms (Varimax), and finally, we apply Kaiser selection criteria considering only factors with Eigen values larger than one (see Afifi et al. 2004 for a practitioner's handbook on these methods). The resulting factors are used to construct the RDI. However, the weights that represent the 'relative social value' attached to each factor are unknown and have to be estimated. This is possible using relative net migration flows, in and out of a given sub-region: by making a decision to migrate, people implicitly weight the importance of regional characteristics that define the local quality of life (QoL). By doing this, we follow the wealth of research that focuses on the relationship between migration and QoL. The basic idea is simple: people do move (migrate) where their QoL is better. Since the seminal article of Tiebout (1956) that lays the theoretical foundations, emphasising that "if consumer-voters are fully mobile the appropriate local governments, whose revenue-expenditure patterns are set, are adopted by the consumer-voters" (Tiebout 1956: 424), papers using migration-based assessments of QoL flourished. Some more recent empirical applications include: Douglas and Wall (1993) – using a non-parametric approach to construct QoL rankings using utility-maximising migration decisions in Canada; Douglas and Wall (2000) – use migration data to observe how much the QoL is determined by income versus non-pecuniary amenities; Nakajima and Tabuchi (2011) – analyse the convergence of migration based utility differentials in Japan; Wirth (2013) - ranks German regions based on interregional migration data and estimates regional utility differentials; and finally. Michalek and Zarnekow (2012) – the paper closest to our research – applies the technique to analyse rural regions of Poland and Slovakia. In their paper focusing on alternative solutions to derive the RDI index. Michalek and Zarnekow (2012c) propose 4 models[2] in order to estimate the weights of regional characteristics. Considering the data available and the purpose of the research, we employ model 1 in this paper. i.e. we estimate the migration function in a balanced panel setting as follows (eq. 1):

$$mp_{it} = \alpha_0 + \beta_k F_{ikt} + v_i + \varepsilon_{it}. \qquad (1)$$

where mp_{it} is the net migration into sub-region i, normalised by the total population of the sub-region i, α_0 is a constant F_{ikt} the value of factor k in sub-region i, at time t. Thus. β_k accounts for the impact of factor k (F_k) upon net migration, and it will be used as a weight in the construction of RDI. Finally, v_i is the region specific residual and ε_{it} is the residual with the usual white noise properties. Given the panel nature of data, and the strict underlying assumptions of panel models, a variety of models will be estimated using specification and diagnostic tests in order to select the 'best' model (see e.g. the handbook of Baltagi. 2008). We may now estimate the RDI index which takes the following form:

$$RDI_{it} = h(\beta_{kt}.F_{ikt}) = \Sigma_k \beta_k{}^* \, F_{ikt}. \quad \text{where} \qquad (2)$$

[2] In Michalek and Zarnekow (2012) Model 2 extends Model 1 to account for spatial autocorrelations. Model 3 incorporates migration related transaction costs. and Model 4 uses information with respect to the *destination region* of migration to compute RDI differentials.

RDI_{it} – Rural Development Index in region *i* and year *t*, F_{ikt} the factors as defined under eq. 1., β_{kt} the weights for each factor specific for region *i*, and time *t* resulting from the estimation of the migration function (1). That is, eq. 2 calculates the RDI as the *proportion* of migration flows explained by local characteristics represented by the factors.

III.2. Convergence analysis
In its simplest form (see Hall et al., 1997 for a discussion of convergence in economic variables), convergence of two time series Xt and Yt might be defined as:

$$\lim_{t\to\infty}(X_t - \vartheta Y_t) = \alpha \; \lim_{t\to\infty}(X_t - \vartheta Y_t) = \alpha \qquad (3)$$

Where α is a stochastic constant (possibly equalling 0, i.e. absolute convergence). Since (3) requires the two series to move exactly together in time, a weaker version of convergence is given by the stochastic convergence, equation (4):

$$lim_{t\to\infty}E(X_t - \vartheta Y_t) = \alpha \qquad (4)$$

Empirical testing of convergence poses a number of challenges. Most research uses the time series properties of (time series or panel) data, in order to test for unit roots in the series. There are, however, other approaches as well, such as dynamic distribution approach (e.g. Cavallero. 2011) or using principal component analysis within a common factor framework (e.g. Becker and Hall. 2009). In its simplest form. stochastic convergence is tested by univariate unit root (UR) tests. Unit root stationarity equals mean reverting behaviour, i.e. shocks resulting deviations from long-run equilibrium will eventually die out.

Panel unit root tests however proved to have superior power to univariate tests and may incorporate larger number of countries if the time dimension of panel is sufficiently long. At this point, it is not the scope of this paper to extensively discuss the theoretical methodology of panel unit root tests. Bearing in mind the sensitivity of unit root tests on specifications (e.g. deterministic components, lags) we employ a bunch of panel unit root tests to achieve robustness. For more details with respect to panel

UR testing methodology, we refer the reader to Maddala and Kim (1998) and Pesaran (2007).

The concept of Beta convergence originates from neo-classical growth models, and if holds, it follows that less developed regions are growing (or developing) faster than more development ones, and thus there is a catch-up process. Equation 5 is estimated in a panel setting, for different time spans to test beta convergence:

$$\frac{1}{T}\ln(y_{iT}/y_{io}) = a - [(1-e^{-\beta T})/T]\ln(y_{io}) + w_{i,0T} \tag{5}$$

If the estimated $-[(1-e^{-\beta T})/T]$ coefficient is smaller than zero, we have evidence for (absolute) convergence, otherwise for divergence. Equivalently, if Beta>0 we have unconditional convergence, and divergence otherwise.

Another indicator of convergence is sigma convergence; this simply measures whether disparities within regions decrease in time or not. Beta convergence is a necessary, yet not sufficient condition of sigma convergence. In this paper, we use the yearly coefficient of variation (standard deviation divided by mean) to assess sigma convergence.

Data and preliminary analysis

To derive the RDI, we use the Hungarian Central Statistical Office's T-STAR[3] regional database provided by Databank of Centre for Economic and Regional Studies of Hungarian Academy of Sciences. We employ the maximum number of indicators (132 variables) available for all localities for all years covering various fields of QoL including demographics (15 variables), health services (9), business units (2), tourism and catering (9), retail sector (24) transport (7), community infrastructure (14), environment (4), culture (2), unemployment (4), education (16), social protection (17) personal income tax (3), number of houses (5), number of villages (1). We summarize the local data available for 3,164 administratively independent settlements

[3] T-STAR is database system of the Hungarian Central Statistical Office collecting the most important settlement statistics for all Hungarian localities. by time and group of statistics.

into 174 LAU1 sub-regions (a much deeper perspective than the 20 regions available under the NUTS-3 nomenclature), the subject of our analysis.

Empirical results

The strategy we follow to derive the RDI indicators is somewhat similar to the one applied by Michalek and Zarnekow 2012 for the construction of Rural Development Index for Poland and Slovakia using 991 local indicators for the former and 337 for the latter. Whilst a number of approaches exist for the selection of variables and indeed construction of a development index (see Michalek and Zarnekow 2012 for excellent review discussing the pros and cons of these methods), selection bias and subjective weighting are likely to affect most processes. Thus, we "let the data choose" and use all variables listed under the data section of this paper. A key issue is the normalisation of variables. To increase the robustness of our results, we use two normalisations, ultimately resulting in two RDI indices. First, we normalise all variables by the total population of the sub-region, and second, we repeat the normalisation using the area (measured in hectares) of the given LAU1 sub-region. Variables normalised by population were grouped in 24 factors[4], some heterogeneous, with high number of variables, others more homogenous with low number of variables (minimum 2). Variables normalised by the area of LAU1 regions were concentrated into much less, 6 factors only.

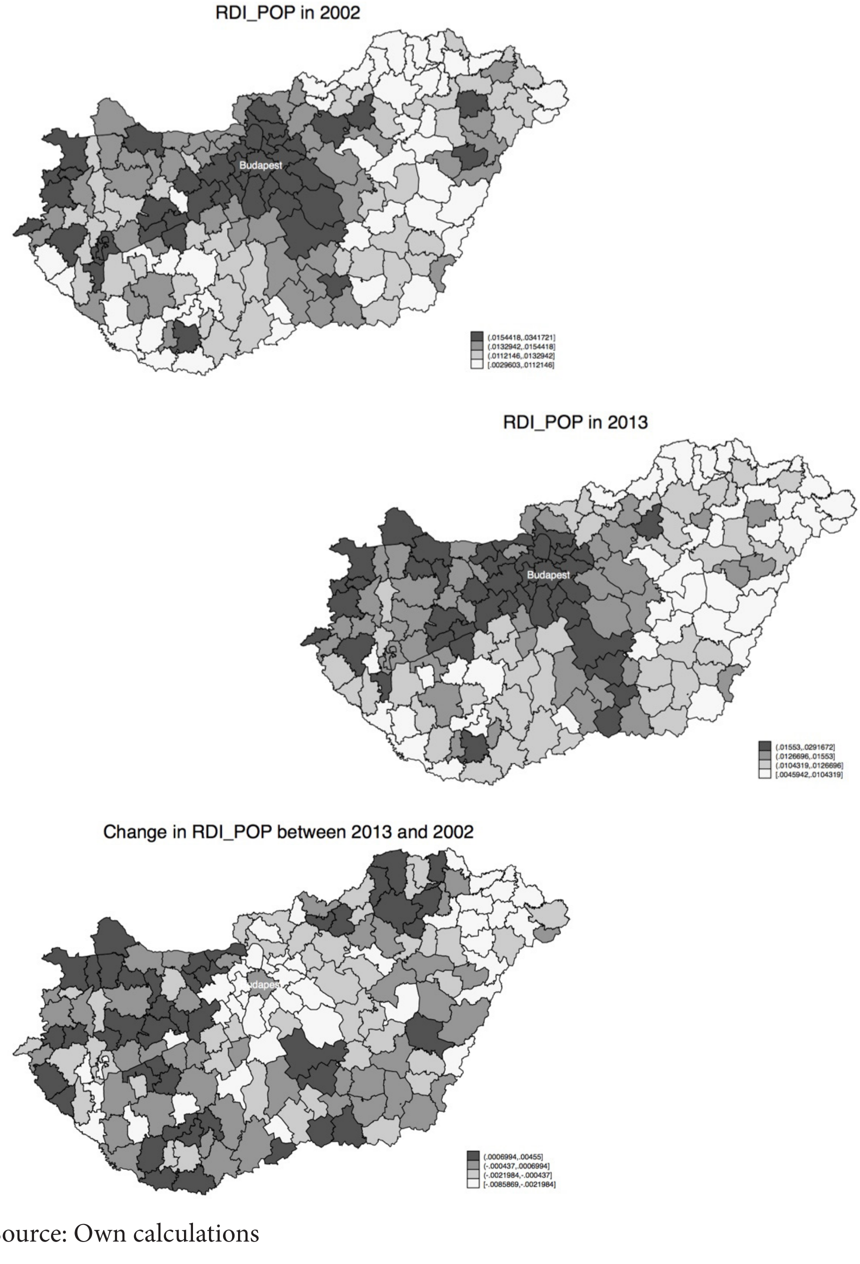
For both sets of factors, equation 1 was estimated as fix and random effects, the Hausman test however rejected the random effects model in both cases (chi2(24) = 266.66, p=0.000 and chi2(6)=50.42, p=0.000 respectively). The modified Wald test for group heteroscedasticity (Green 2000, pp. 598) in fixed effects model rejected the homoscedasticity assumption (chi2(174)=4341.77, p=0.000 and chi2(174)=4778.76, p=0.000 respectively). Similarly, the Pesaran (2004) test rejects the null of cross-section independence (p=0.000 and p=0.000 respectively). Further, the Wooldridge (Wooldridge 2002; Drukker 2003) test for first order autocorrelation in panel data also rejected the null (F(1,173)=80.977, p=0.000 and

[4] Variables with loadings above 0.4 were retained after rotation.

F(1,173)=107.772, p=0.000 respectively). Thus, linear regression methods with panel-corrected standard errors assuming heteroscedastic and contemporaneously correlated disturbances across panels were used. Regression results are presented in tables A1 and A2 in the Annex. We denote the derived indices RDI_POP and RDI_AREA respectively. The correlation coefficient between the two indices ranges from 76.8% in 2013 to 81.7% in 2007.

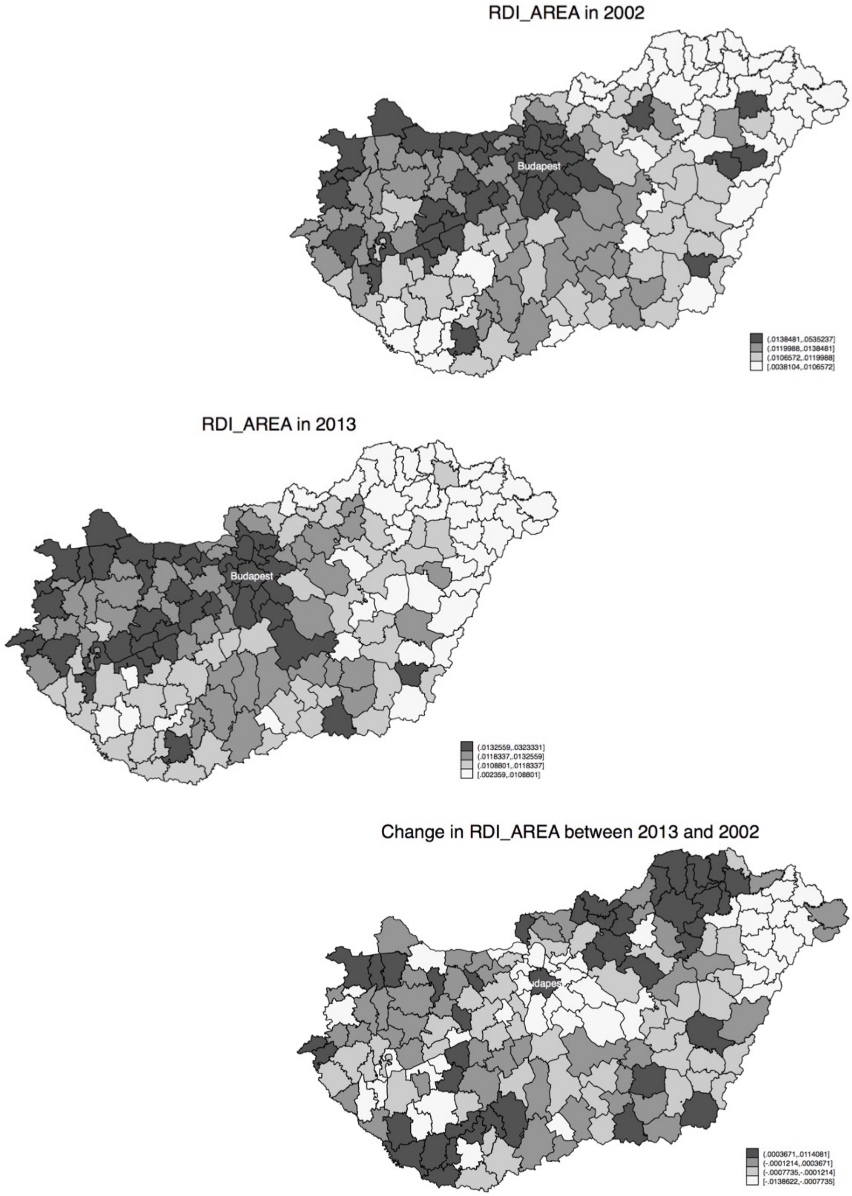
Figures 1 and 2 present regional development maps for RDI_POP and RDI_AREA indices in 2002, 2013 and the change in RDI between 2013 and 2002 respectively. Development levels are sorted into quantiles, the top quantile being the darkest, the lowest quantile the lightest shade. Despite major differences in the way they were calculated, maps depicting the two RDI indices are remarkably similar, both confirming intuition. Central and North-West Hungary are the most developed whilst Eastern, North-Eastern and South-West sub-regions are doing the worst. Graphical evidence does not suggest major differences with respect of the distribution of development levels across LAU1 sub-regions in 2002 and 2013. The most and least developed regions are similar in both 2002 and 2013. If, however, the difference between the end and start period is analysed (3rd graph of Figs 1 and 2), it is evident, that at least some of the least development regions increased their comparative development levels (in the North and South-West). In the same time, the already highly developed region of Central Hungary increased the least its relative development level, in accordance with the aims of the development policy. Unfortunately, the latter is also true for the poorest, North-East regions that do not seem to catch up with the rest of LAU1 regions.

Figure 1. Levels of development in 2002, 2013 and the change between, measured by RDI_POP



Source: Own calculations

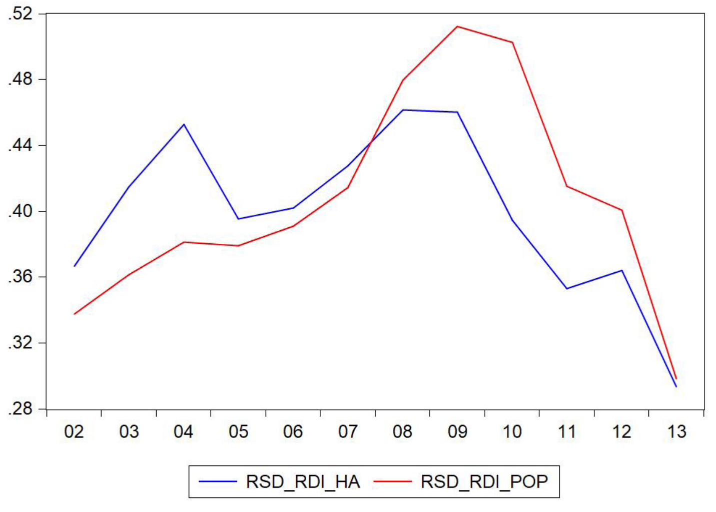
Figure 2. Levels of development in 2002, 2013 and the change between, measured by RDI_AREA



Source: Own calculations.

Next, we proceed to the convergence analysis, starting with the simplest of indicators, sigma convergence. For both indicators, yearly standard deviation and mean values were calculated and their ratio depicted in Fig. 3. Based on the graph, it would be hard to draw conclusions with respect to sigma convergence for the full period. The RDI_POP displays a more even evolution, but both indices suggest periods of divergence (until 2009) convergence (after 2009).

Figure 3. Relative standard deviation of RDI_POP (RSD_RDI_POP) and RDI_AREA (RSD_RDI_HA) regional development indices



Source: Own calculations.

Beta convergence is estimated using equation 5. Considering the volatile results of sigma convergence, and since a large panel dataset is available, we use sequential estimation technics. Results of beta convergence of logged RDI indices are presented in table 1, and table 2. The first column presents the estimates of the constant *(a)* followed by its standard error. Column three and four lists the estimates of *beta* and it standard error respectively. We start using 3 years of data (number of observation in the panel regression is depicted in the last column of tables), the RDI_0 always being the one representing the start period, i.e. 2002. Thus, the last row of each table, measures the entire convergence process between 2002 and 2013. With the exception of the first beta estimate for RDI_POP, all other estimates are significantly different from zero. The magnitude of estimated coefficients, is consistent across different sample sizes and it is comparable between the two indices, ranging between 0.02 and 0.04. More importantly, however, all estimations are positive, suggesting divergence rather than convergence.

Table 1. Sequential estimates of beta convergence for RDI_POP

Cons	SE_cons	Beta	SE_beta	Obs.
0.117	0.055	0.019	0.013	522
0.103	0.042	0.020	0.010	696
0.084	0.034	0.018	0.008	870
0.097	0.028	0.022	0.007	1044
0.122	0.025	0.029	0.006	1218
0.142	0.023	0.035	0.005	1392
0.168	0.022	0.042	0.005	1566
0.156	0.020	0.040	0.005	1740
0.142	0.018	0.037	0.004	1914
0.120	0.017	0.031	0.004	2088

Note, the coefficient of logRDI (measured at the beginning of the period) displayed in column 3 is $-[(1-e^{-\beta T})/T]$, thus the requirement to be negative for convergence.
Source: Own calculations.

Table 2. Recursive estimates of beta convergence for RDI_AREA

Cons	SE_cons	Beta	SE_beta	Obs
0.199	0.035	0.042	0.008	522
0.158	0.025	0.034	0.006	696
0.137	0.021	0.030	0.005	870

Table 2. Recursive estimates of beta convergence for RDI_AREA

Cons	SE_cons	Beta	SE_beta	Obs
0.135	0.018	0.030	0.004	1044
0.140	0.016	0.032	0.004	1218
0.146	0.015	0.034	0.003	1392
0.142	0.014	0.033	0.003	1566
0.125	0.013	0.029	0.003	1740
0.120	0.012	0.028	0.003	1914
0.101	0.011	0.024	0.003	2088

Note, the coefficient of logRDI (measured at the beginning of the period), displayed in column 3 is $-[(1-e^{-\beta T})/T]$, thus the requirement to be negative for convergence.
Source: Own calculations.

A further stream of empirical analysis is offered by the possibility of testing economic convergence along with club clustering (Phillips and Sul, 2007; 2009). These tests were recently implemented in STATA (Du, 2017), but in this application provided no additional results, since all 174 sub-regions the subject of this analysis were clustered in a single club.

The final convergence tests are the panel unit root tests. The null hypothesis of all tests presented in tables 3–6, is I(1) processes, i.e. unit root. Unless the null is rejected, there is evidence for divergence of regional development levels. Tables 3–4 presents first and second-generation panel unit root test results without trend (table 3) and with trend (table 4). RDI_POP seems stationary (except for the Phillips-Perron test) when only individual effects are considered. For RDI_AREA only the LLC test rejects the null of unit root with the specification above. When however, a trend[5] is added to the test regression, all tests point towards non-stationarity, i.e. divergence of RDI indices across sub-regions.

[5] Whilst test regressions are rather difficult to retrieve from modern econometric packages, we do not have a significance of the trend in these regressions. Graphical evidence and a simple regression on a trend however suggest, RDI indices are upward trending, thus a unit root test equation with individual effects and trend seems appropriate.

Table 3. Panel unit root tests with individual effects

	RDI_POP Statistic	Prob.**	**RDI_AREA** Statistic	Prob.**	Cross-sections	Obs.
Null: Unit root		(assumes common unit root process)				
Levin. Lin & Chu t	-11.9464	0.0000	-6.8001	0.0000	174	1847
Null: Unit root		(assumes individual unit root process)				
Im. Pesaran and Shin W-stat	-4.54643	0.0000	-0.98264	0.1629	174	1847
ADF - Fisher Chi-square	425.837	0.0027	333.426	0.7037	174	1847
PP - Fisher Chi-square	277.883	0.9977	314.587	0.9004	174	1914

Source: Own calculations

Table 4. Panel unit root tests with individual effects and linear trend

	RDI_POP Statistic	Prob.**	**RDI_AREA** Statistic	Prob.**	Cross sections	Obs.
Null: Unit root		(assumes common unit root process)				
Levin, Lin & Chu t*	-1.29987	0.0968	0.75760	0.7757	174	1867
Breitung t-stat	7.69686	1.0000	12.3213	1.0000	174	1693
Null: Unit root		(assumes individual unit root process)				
Im, Pesaran and Shin W-stat	5.04307	1.0000	6.95697	1.0000	174	1867
ADF - Fisher Chi-square	284.735	0.9944	267.075	0.9995	174	1867
PP - Fisher Chi-square	221.917	1.0000	317.558	0.8778	174	1914

Source: Own calculations

Panel unit tests may, however, pose additional challenges when cross sectional dependence is also considered. The Maddala and Wu (1999) test assumes cross sectional independence, whilst the Pesaran (2007) test assumes the cross-section dependence is in the form of a single unobserved common factor. Table 5 presents MW test results for both indices with and without trend, whilst table 6 depicts Pesaran (2007) test statistics and their p-value, similarly, with and without a trend. In addition, we run the test regression with various lag specifications, from 0 to 2. With trend, the MW test cannot reject the divergence null for any of the indices. Without trend and one lag, the RDI_POP seems to be the only stationary process. Pesaran (2007) tests in table 6 largely reinforce previous findings (only without lags is RDI_POP stationary assuming individual effects only).

Table 5. Maddala and Wu (1999) Panel Unit Root tests

Variable	lags	chi_sq	p-value	chi_sq	p-value
Null: Unit root		Without trend		With trend	
rdi_pop	0	263.688	1.000	172.992	1.000
rdi_pop	1	505.100	0.000	343.616	0.556
rdi_pop	2	357.049	0.357	181.654	1.000
rdi_area	0	307.889	0.940	271.801	0.999
rdi_area	1	278.461	0.998	195.415	1.000
rdi_area	2	344.000	0.550	156.179	1.000

Source: Own calculations

Table 6. Pesaran (2007) Panel Unit Root tests

Variable	lags	Zt-bar	p-value	Zt-bar	p-value
Null: Unit root		Without trend		With trend	
rdi_pop	0	-8.200	0.000	-4.936	0.000
rdi_pop	1	-0.686	0.246	4.848	1.000
rdi_pop	2	2.187	0.986	46.540	1.000
rdi_area	0	-5.019	0.000	0.331	0.630
rdi_area	1	2.564	0.995	6.607	1.000
rdi_area	2	4.188	1.000	46.690	1.000

Source: Own calculations

In summary, unit root tests indifferent of specification or econometric mechanism, largely confirm the results of sigma and beta convergence, i.e. that there is no convergence at LAU1 level of the indices measuring the local development.

We may conclude – and that's a quite unfortunate result – that Hungarian sub regions present extremely low mobility patterns, i.e. they are unlikely to improve positions, reinforcing previous findings of non-convergence.

Conclusions

The analysis of sub-regions and econometric estimations reveal several main findings. First, it highlights the importance and methodological difficulties with respect to the creation of s complex local development indicator at low aggregation levels, where the usual variables employed, such as GDP are not available. Second, we could not find serious evidence in favour of convergence in regional development levels of Hungarian sub-regions during the 12 years in our focus. Anecdotic evidence of some Hungarian LAU1 and even NUTS3 falling seriously behind originating from applied development scientists, development project managers and sociologists working on the field has existed, but, to the best of our knowledge, this paper is the first that uses econometric methods to test low aggregation level convergence.

Our results are even more disappointing (at least when general wellbeing or the impact of development policy is considered) when one considers that except for the first two years of our time span, Hungary had generous access to the EU Cohesion funds, meant exactly to close the gap between regions. In addition, one may ask, if the building blocks of larger (NUTS1, NUTS2) regions are diverging in development, how will it be possible to achieve a cross-EU convergence? Clearly, this paper comes with some caveats that are also opportunities to take this research forward. First, spatial effects were not considered in this application, whilst new advances in spatial econometrics emphasise the importance of spatial AR and MA models, including spatial variables (or lags) in the beta convergence test equation may yield different results, or at least highlight positive and negative spillovers between sub-regions. Second, alternative ways of index construction are also feasible (e.g. following the methodology the

Hungarian Government is using by creating simple averages of much less local variables than employed here), these would insure easier replicability of the models should new datasets become available, yet with the price of losing the 'objectivity', i.e. 'let the data choose' properties of present index. Further, newly available datasets include not only in and out-migration from sub-regions, but also the destination and provenience of within nation migrants. This would allow the estimation of a more complex and robust index through a migration function using the differentials of factor values representative of origin and destination sub-regions.

Finally, our results only fuel the larger scale debate with respect to macroeconomic convergence of regional development (or income) levels, that, by now, has plenty of pro and contra papers published with continuously renewed methodology.

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