Regional Convergence and Growth Clusters in Central and Eastern Europe: An Examination of Sectoral-Level Data

Scott W. Hegerty
Department of Economics, Northeastern Illinois University
5500 N. Saint Louis Ave, Chicago, IL USA 60625
s-hegerty@neiu.edu
773-442-5695

Reviewers:
Dimitrios DAPONTAS, University of Peloponnese, Greece;
Katalin LIPTÁK, University of Miskolc, Hungary;
Olena SOKOLOVSKA, Institute Of Industrial Economics of National Academy of Sciences of Ukraine, Ukraine.

Abstract
Neoclassical growth theory suggests that individual Central and Eastern European (CEE) regions should converge with one another, as those with low initial levels of per-capita GDP grow faster than regions with high initial levels. But previous studies show convergence is more likely to occur at the national level than the regional level. In addition, sectoral analysis (particularly in "new economy" industries such as finance) might uncover results that are not found using aggregate data. This study uses spatial regression and "hot spot" analysis for 233 NUTS-3 regions and four individual sectors from 2000 to 2013, testing for regional convergence and the presence of growth clusters. A regression of growth in per-capita gross value added (GVA) on initial levels finds no evidence for "beta convergence," except for in the construction sector at the country level in a few cases. Growth "hot spots" are found using the Getis-Ord G^* statistic for growth for all sectors except industry in the Baltics and for all sectors in Bulgaria and Romania. Low-growth "cold spots" are located in Poland and Croatia. These findings suggest ideal destinations for investment.

Keywords: Regional Convergence; Central/Eastern Europe; Spatial Statistics; Gross Value Added

JEL classification: R12, P2

Introduction

With their continued transition from centrally planned economic systems and accession to the European Union, the nations of Central and Eastern Europe (CEE) have seen living standards improve markedly in recent decades. Yet, while their economies have tended to converge toward the EU averages, it is possible that this process might not be the case at the regional level within each country. In fact, with foreign direct investment (FDI) often concentrated in wealthier cities, and educated workers attracted to these same metropolitan areas, certain regions might "pull away" from their worse-performing neighbours. Combined with economic restructuring, which has led to growth in services and producer services at the expense of agriculture and manufacturing, it is possible that regional growth might diverge over time, particularly for certain sectors of the economy.

This study examines the neoclassical theory of regional convergence, which predicts that over time the poorer individual sub-units within CEE nations might grow faster than the richer ones. Modelling growth rates as functions of initial gross value added (GVA) per capita, we might expect negative coefficients if countries with lower GVA in 2000 have faster growth rates from 2000 to 2013. The purpose of this paper is to test this hypothesis not just for all CEE regions at the aggregate level, but also for four economic sectors (agriculture; construction; industry; and finance, insurance, and real estate). We expect that certain nontradeable sectors (such as construction) to behave differently than high-tech, "new economy" industries. In fact, we find stronger evidence for convergence at the sectoral level than at the aggregate level. We test this convergence hypothesis both econometrically and with spatial statistical models to find sectoral "clusters" where regions of high or low growth rates are located near one another. We also test for convergence within individual countries.

Overall, we find little evidence of convergence, except in certain cases for individual countries and sectors. We do, however, uncover certain growth clusters, particularly in the Baltics, that are worthy of further examination.

This paper proceeds as follows: Section II discusses the relevant literature. Section III outlines the model, and Section IV discusses the results. Section IV concludes.

Review of the Literature

Much the literature on regional income convergence is based on the work of Barro and Sala-i-Martin (1991), whose neoclassical approach relies on the concept of diminishing Marginal Productivity of Capital (MPK) and assumes that capital is mobile. The model also assumes exogenous technical progress, full employment, and a fixed labour-force participation rate. As such, differences in capital drive the model in the context of a Cobb-Douglas production function of the type $Y = AK^{\alpha} L^{B}$ with output (Y) a function of Capital (K), Labour (L), and technology (A). Decreasing MPK is the result of the parameter $\alpha < 1$, so that the

Hegerty S.W. 2016. Regional Convergence and Growth Clusters in Central and Eastern Europe: An Examination of Sectoral-Level Data. *Eastern European Business and Economics Journal* **2(2)**: 95-110.

derivative $\partial Y / \partial K < 1$. As such, regions low initial levels of development will have higher rates of return, attracting capital from wealthier regions. This leads to so-called "beta convergence," or β-convergence, after the coefficient from a regression of growth rates on initial levels. An additional measure, called sigma convergence or σ-convergence, reflects declining dispersion among regional per-capita incomes. The authors test U.S. personal income in a sample that begins in 1880, and gross state product beginning in 1963, and also examine European data. Their study finds evidence of regional convergence.

Sala-i-Martin (1996) also explains conditional β-convergence, which also includes additional explanatory variables in the regression model. Examining countries worldwide at the national level, as well as U.S. states, Japanese prefectures and European regions, the authors arrive at a convergence rate of about 2% per year. Tsionas (2000) finds evidence of convergence in Total Factor Productivity (TFP), or A above, for the EU-15 over the period from 1960 to 1997. The author finds convergence, particularly among certain core countries. On the other hand, Boldrin *et al.* (2001) also studying the EU-15, uncover regional disparities in the EU15 and calls for policies to reduce them.

A number of studies have examined growth and convergence at the sectoral level. Le Gallo and Dall'erba (2008) examine labour productivity (per-capita GVA) for 145 European regions over the period from 1975 to 2000 in five different sectors: agriculture, energy and manufacturing, construction, market services, and non-market services. The authors find that energy and market services converge to the same steady state, but that agriculture, construction, and non-market services have regional steady states. The speeds of convergence and spatial effects also vary by sector. Corrado *et al.* (2005) study per-capita GVA convergence clusters in Western Europe from 1975 to 1999 in agriculture, manufacturing, market services, and non-market services by testing for multivariate stationarity. The authors note the changing dynamics of convergence. Villaverde and Maza (2008) examine 10 sectors in the EU-15 from 1980 to 2003. The authors uncover weak evidence of β-convergence, but also test for spatial autocorrelation and clusters via Moran's I and local Moran's I, which calculate relationships between variables within each region versus those of their neighbours.

These theories have been tested empirically for a number of regions, using a variety of advanced statistical procedures. Le Gallo and Ertur (2003) apply Moran's I and the Getis-Ord G statistic to find evidence of spatial autocorrelation and spatial disparities in regional per capita GDP for 138 Western European regions from 1980 to 1995. Noting the presence of geographic clusters, the authors emphasize the importance of proper estimation techniques. At the individual country level, Dall'erba (2005) examine 48 Spanish regions from 1980 to1996.

Le Gallo and Dall'erba (2006) discover a "convergence club" on Europe's periphery (in this case, Southern Greece, since CEE regions were not included in the study) testing a Seemingly Unrelated Regression model with spatial autocorrelation for two sub-periods (1980–1989 and 1989–1999) for 145 European regions, from 1980 to 1999. Olejnik (2008) applies a spatial Autoregressive Distributed Lag (ARDL) dynamic model, for 228 EU NUTS-3 regions, to explain convergence up to 2004.

Nonparametric methods, which make fewer assumptions of the underlying distributions of geographic data and allow for nonnormality, are becoming increasingly popular. Applying kernel estimation, Ezcura and Rapún (2007) examine labour productivity for 250 NUTS-2 regions from 1991 to 2003 and find that the CEE countries form a second "node" around which convergence occurs, in addition to the core countries. Sassi (2010) applies Geographically Weighted Regression (GWR) in a study of 166 EU-15 regions from 1995 to 2005. Focusing on agriculture, the author finds no unique convergence in the region, and suggests that the neoclassical convergence theory be rejected in favour of alternative theories such as the "New Economic Geography." Azomahou et al. (2011) study 255 EU regions in a semiparametric analysis that spans the period from 1998 to 2007. Because the convergence process is shown to be nonlinear by income, which richer and poorer regions exhibiting different convergence processes, this semiparametric method is thought to perform better than parametric methods.

Studies that focus on the CEE region have also found limited evidence of convergence. Petrakos (2001) emphasizes the roles of foreign capital, trade, and structural change in driving the process. Using regional data for FDI, GRP per capita, and investment per capita data for Poland, Hungary, Romania, and Bulgaria, he finds mixed results. Hungary exhibits divergence in (Gross Regional Product) GRP per capita, while Poland shows weak convergence. Other variables are also mixed: FDI and investment both register divergence for Poland. Metropolitan areas, as well as regions that border the West, benefit from transition. Petrakos and Economou (2002) focuses explicitly on Southeast Europe, finding

Hegerty S.W. 2016. Regional Convergence and Growth Clusters in Central and Eastern Europe: An Examination of Sectoral-Level Data. *Eastern European Business and Economics Journal* **2(2)**: 95-110.

further evidence of divergence, as well as the metropolitan-area and border effects shown above. Ezcurra and Pascual (2007) study 39 CEE regions from 1992 to 2001, and find evidence of convergence between countries, but divergence between regions. Artelaris *et al.* (2010) calculate weighted coefficients of variation for 10 CEE countries, isolating convergence "clubs" over the period from 1990-2005. Tselois (2009) examines 102 regions from 1995 to 2000. The author estimates an expanded model that controls for other variables (such as employment) and includes spatial effects; he finds evidence of convergence in income per capita in the region.

More recently, Petrakos *et al.* (2011) apply linear and non-linear OLS and Weighted Least Squares (WLS) to test regional convergence models for 249 NUTS-3 regions from 1990 to 2003. As was shown by the semiparametric methods mentioned above, the authors find a nonlinear process by which convergence occurs early on, with divergence following at higher stages of development. Mikulić *et al.* (2013) examine the relationship between the EU and Croatia for NUTS-2 and -3 regions from 2001 to 2008. Again, national convergence is stronger than regional convergence, since the former β is lower than the latter.

Regional analyses of CEE countries for specific sectors, or those that use geospatial methods, are most relevant to our current study. Mora *et al.* (2004) discuss the effects of economic integration on industry concentration for newly admitted EU members. Smętkowski and Wójcik (2012) examine NUTS-3 data from 1998 to 2005 and note the presence of national-level convergence and regional divergence, particularly due to the influence of capital cities. Their spatial autocorrelation analysis shows polycentric development and the presence of growth poles. Their local Moran's I statistics show clusters of high growth in the Baltics and low growth in Eastern Poland, with Eastern Bulgaria and Romania also split. Chapman et al. (2012) include nonparametric methods as well as Moran and local Moran statistics in their analysis of new EU member states, and find evidence of a new "convergence club."

This study extends these analyses to examine recent data, both at the aggregate level and for four separate sectors, using geospatial statistical techniques. While we find little evidence of sectoral convergence for the entire CEE region, we do find industry-specific results and growth "clusters," particularly in the Baltics. These results are useful for economic development, particularly with the goal of helping to determine appropriate destinations for investment. Our methods and results are explained below.

Methodology

Using the EUROSTAT database, we extracted data at the NUTS-3 level for 238 national subregions in the CEE region for the period from 2000 to 2013. The countries examined include Bulgaria, Croatia, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia. Per capita GVA values are calculated, in Euros, by dividing by population for each region. Values are calculated both at the aggregate level and for the agricultural, construction, industrial, and FIRE (finance, insurance, and real estate) sectors. We then calculate growth rates from 2000 to 2013 as the ratio of the later value to the earlier value. Because of data limitations, 2012 values are used for the construction sector.

Since we expect growth rates in each region to be related to growth rates in neighbouring regions, we first test for spatial autocorrelation using Moran's I statistic. This value compares local values with the value's mean, as follows:

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

The weight matrix w is assigned to the regions' neighbours, generally with more distant locations given less weight. While the choice of weighting scheme is subject to debate, we follow LeSage (2014) and follow a simple scheme that does not require a large matrix. Known as "Queen contiguity", neighbouring regions (even at corners, as in the chess piece's range of motion) are given full weight while other regions receive zero weight. We choose an order of one, meaning that only directly contiguous regions are considered to be "neighbours." This statistic can be evaluated as a standard autocorrelation function, with the exception that the expected value is -1/(1-n) rather than zero.

Next, we test for β-convergence—the hypothesis that regions with low initial per-capita GVA will grow faster than regions with high

Hegerty S.W. 2016. Regional Convergence and Growth Clusters in Central and Eastern Europe: An Examination of Sectoral-Level Data. *Eastern European Business and Economics Journal* **2(2)**: 95-110.

per-capita GVA. This negative relationship will result in a significantly negative coefficient in the following regression:

$$\frac{y_t}{y_0} = \alpha + \beta y_0 + \varepsilon \tag{2}$$

Since growth rates are spatially dependent, we estimate this equation using a spatial lag model, which uses the same weight matrix as above:

$$y = \rho W y + X\beta + \varepsilon \tag{3a}$$
$$(I - \rho W)y = X\beta + \varepsilon \tag{3b}$$
$$y = (I - \rho W)^{-1}(X\beta + \varepsilon) \tag{3c}$$

We estimate these equations for aggregate GVA per capita. This model will provide more accurate results than traditional models such as Ordinary Least Squares. While our focus is on the entire CEE region as a whole, we also estimate this model for individual countries (or, where the number of regions is small, for country groups or pairs). Individual estimations are performed for Poland, Hungary, Bulgaria, and Romania, as well as group estimations for the Baltics, the Czech Republic and Slovakia, and Croatia and Slovenia.

Finally, we use spatial statistical methods to look for growth "clusters" ("hot spots" or "cold spots"), regions where high or low growth rates are located in geographic proximity to one another. This is done using the Getis-Ord G^* statistic to compare each region's growth rate with those of its neighbours:

$$G_i^* = \frac{\sum_j^n w_{ij} x_j - \bar{x} \sum_j^n w_{ij}}{s_x \sqrt{\frac{n \sum_j^n w_{ij}^2 - \left[\sum_j^n w_{ij} \right]^2}{n-1}}} \tag{4}$$

We can map and analyse regions with significant G^* statistics. Our results are provided below.

Hegerty S.W. 2016. Regional Convergence and Growth Clusters in Central and Eastern Europe: An Examination of Sectoral-Level Data. *Eastern European Business and Economics Journal* **2(2)**: 95-110.

Results

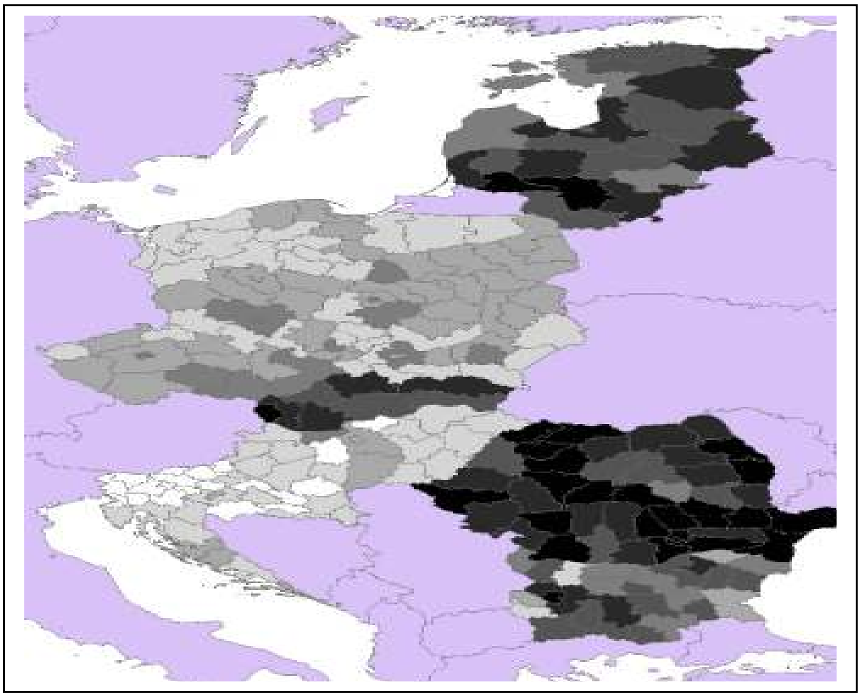
Table 1 presents the Moran's *I* statistics for each of the GVA growth rates used in this analysis. We find that aggregate rates are the most spatially autocorrelated. Growth in one region, therefore, is related to growth in adjacent areas. At the sectoral level, this effect is weaker, but still sufficiently strong to require that our estimations control for these relationships. FIRE has the highest autocorrelation statistic, suggesting that growth in producer services is most likely to cluster by region.

These aggregate growth rates are mapped in Figure 1.

Table 1. Moran's I Statistic for Spatial Autocorrelation

Variable	Statistic
Aggregate	0.773
Agriculture	0.357
Industry	0.496
FIRE	0.701
Construction	0.548

Fig. 1. Aggregate GVA Growth, 2000-2013, By NUTS-3 Regions



Hegerty S.W. 2016. Regional Convergence and Growth Clusters in Central and Eastern Europe: An Examination of Sectoral-Level Data. *Eastern European Business and Economics Journal* **2(2)**: 95-110.

We see the highest growth rates in Lithuania, Slovakia, and Romania. Most likely this is due to lower starting points, the conjecture that we test throughout this paper. The sector-level growth rates depicted in Figure 2 show that agriculture has similar, but more muted, growth regions in the three countries mentioned previously. Industry shows strong growth in Romania and Bulgaria, while construction growth is weak in Poland and Hungary. FIRE has grown in the Baltics (particularly in Latvia), as well as the Czech and Slovak Republics, Bulgaria, and Romania.

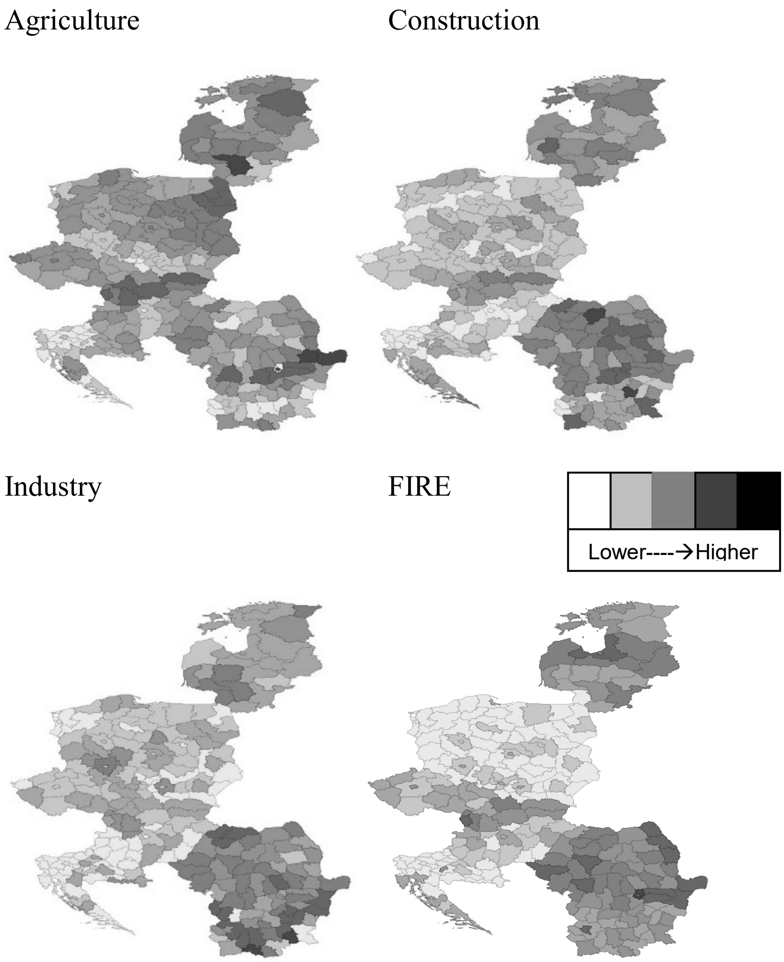


Fig. 2. Sectoral GVA growth by NUTS-3 Regions

Do these growth regions support the idea of regional convergence? To answer this question, we turn to the results of the spatial lag regression

Hegerty S.W. 2016. Regional Convergence and Growth Clusters in Central and Eastern Europe: An Examination of Sectoral-Level Data. *Eastern European Business and Economics Journal* **2(2)**: 95-110.

in Tables 2 and 3. The β coefficient, which must be significantly negative to support the hypothesis, is associated with GVA_2000. We see that this statistic is not significant at the regional level for any industry. We therefore cannot find evidence to support regional convergence in Gross Value Added since 2000.

	Aggregate	Industrial	Agriculture	Construction	FIRE
Variable	Stat(p-value)	Stat(p-value)	Stat(p-value)	Stat(p-value)	Stat(p-value)
Rho	0.848 (0.000)	0.645 (0.000)	0.541 (0.000)	0.671 (0.000)	0.766 (0.000)
C	0.379 (0.000)	1.011 (0.000)	0.844 (0.000)	0.978 (0.000)	0.664 (0.000)
GVA_2000	0.000 (0.319)	0.000 (0.417)	-0.001 (0.693)	-0.001 (0.371)	0.000 (0.795)
R2	0.722	0.404	0.256	0.454	0.625
AIC	298.823	698.77	467.031	786.549	638.278

Table 2: Spatial Lag Regression Results, Regional Level.

When we examine individual countries (or country groups), we do find evidence of within-country convergence for certain sectors. Hungary, in particular, shows evidence of convergence in agriculture and construction, while the former Yugoslav republics of Croatia and Slovenia see their construction and industrial GVAs converge. The Baltics have a significantly negative β coefficient for construction. Most likely, being the one sector that cannot be exported, this sector is the most localized. This finding is worthy of further study.

Finally, we map the Getis-Ord G* statistics by significance level, depicting “hot spots” where high growth cluster (with a significance level of 0.05) and “cold spots” where low growth rates cluster. These are presented in Figures 3 and 4. We find that at the aggregate level, Growth clusters in the Baltics (Latvia and Lithuania, but not Estonia), perhaps because Estonia’s “head start” during the 1990s led to fast growth and convergence before the period of this study. Romania also serves as another “hot spot.” Slow-growth “cold spots” are located in Western Poland, Croatia, and part of Hungary.

Hegerty S.W. 2016. Regional Convergence and Growth Clusters in Central and Eastern Europe: An Examination of Sectoral-Level Data. *Eastern European Business and Economics Journal* **2(2)**: 95-110.

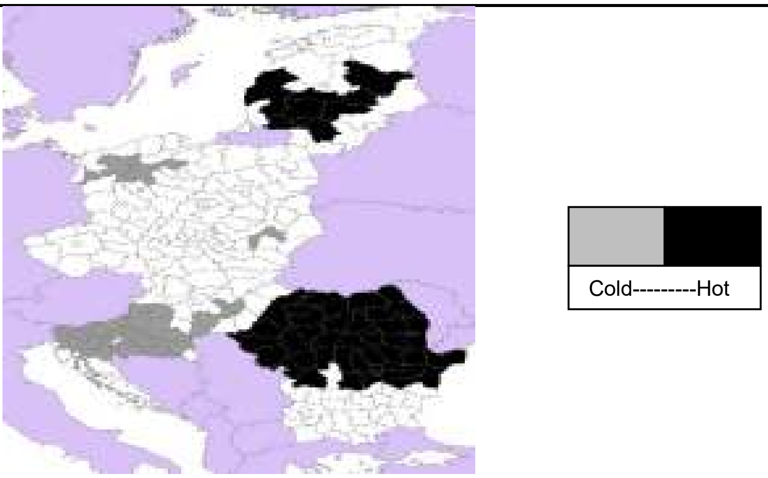
Czech Rep./ Slovakia (N=21)	Aggregate	Agriculture	Construction	Industry	FIRE
Rho	0.821 (0.000)	0.669 (0.000)	0.697 (0.000)	0.583 (0.002)	0.582 (0.002)
C	0.465 (0.084)	0.757 (0.037)	0.789 (0.053)	1.085 (0.020)	1.188 (0.034)
GVA_2000	0.000 (0.921)	-0.001 (0.593)	0.000 (0.578)	0.000 (0.333)	0.000 (0.507)
AIC	19.353	36.342	54.755	23.993	45.398
R^2	0.700	0.491	0.522	0.357	0.328
Poland (N=72)					
Rho	0.404 (0.003)	0.808 (0.000)	0.056 (0.735)	0.081 (0.625)	0.576 (0.000)
C	1.228 (0.000)	0.305 (0.018)	1.99 (0.000)	2.116 (0.000)	0.775 (0.000)
GVA_2000	0.000 (0.429)	0.157 (0.067)	0.000 (0.990)	0.000 (0.170)	0.000 (0.340)
AIC	-37.651	44.116	77.462	96.479	5.898
R^2	0.153	0.683	0.002	0.032	0.256
Hungary (N=20)					
Rho	-0.442 (0.156)	0.211 (0.383)	-0.532 (0.071)	-0.214 (0.500)	-0.617 (0.040)
CONSTANT	2.722 (0.000)	1.329 (0.001)	2.805 (0.000)	2.384 (0.000)	3.326 (0.000)
GVA_2000	0.000 (0.009)	**-0.004 (0.040)**	**-0.002 (0.006)**	0.000 (0.785)	0.000 (0.002)
AIC	-4.899	12.637	13.712	30.776	6.264
R^2	0.243	0.223	0.314	0.028	0.282
Croatia and Slovenia (N=33)					
Rho	0.328 (0.071)	0.492 (0.004)	0.39 (0.016)	-0.017 (0.935)	0.134 (0.546)
CONSTANT	1.366 (0.000)	0.557 (0.015)	1.800 (0.000)	2.350 (0.000)	1.714 (0.000)
GVA_2000	*-0.038 (0.005)*	0.199 (0.436)	**-1.742 (0.001)**	**-0.307 (0.001)**	-0.113 (0.541)
AIC	-10.998	15.586	60.115	54.878	60.752
R^2	0.399	0.289	0.541	0.304	0.029
Baltics (N=21)					
Rho	-0.199 (0.517)	-0.272 (0.377)	-0.197 (0.512)	0.303 (0.233)	0.448 (0.046)
CONSTANT	3.918 (0.000)	3.082 (0.000)	5.764 (0.000)	2.711 (0.004)	1.835 (0.035)
GVA_2000	-0.054 (0.407)	-0.809 (0.623)	**-5.83 (0.008)**	-0.682 (0.244)	0.193 (0.807)
AIC	18.828	60.922	61.300	44.135	63.830
R^2	0.047	0.068	0.275	0.147	0.194
Bulgaria (N=28)					
Rho	-0.093 (0.716)	0.447 (0.027)	-0.207 (0.446)	-0.167 (0.537)	-0.092 (0.683)
C	2.912 (0.000)	0.844 (0.008)	4.114 (0.000)	5.251 (0.000)	3.21 (0.000)
GVA_2000	0.001 (0.000)	-0.009 (0.676)	-0.007 (0.447)	-0.003 (0.612)	0.005 (0.000)
AIC	31.221	32.825	120.333	121.349	32.890
R^2	0.337	0.166	0.039	0.026	0.652
Romania (N=42)					
Rho	0.331 (0.090)	0.37 (0.049)	0.162 (0.455)	0.258 (0.209)	-0.013 (0.957)
C	2.44 (0.001)	1.096 (0.010)	4.273 (0.000)	2.969 (0.000)	4.91 (0.000)
GVA_2000	0.000 (0.107)	1.039 (0.001)	0.006 (0.307)	0.000 (0.994)	0.001 (0.380)
AIC	50.589	106.523	149.292	115.734	144.690
R^2	0.128	0.254	0.056	0.046	0.016

Bold = Significantly negative convergence coefficient

Table 3: Spatial Lag Regression Results, Country Level

Hegerty S.W. 2016. Regional Convergence and Growth Clusters in Central and Eastern Europe: An Examination of Sectoral-Level Data. *Eastern European Business and Economics Journal* **2(2)**: 95-110.

Fig. 3.
Getis-Ord "Hot Spots" and "Cold Spots," Aggregate GVA Growth.



At the sector level, these patterns hold, although the specific subregions within each cluster differ. One particular finding is that Croatia is a low-growth area, and Romania is a high-growth area, for all four sectors In agriculture, the high-growth Baltic sector extends into Estonia, and there is additional, small "hot spot" in Slovakia. The construction "hot spot" in the Baltics centres primarily in Lithuania, while the Czech and Slovak republics now are considered low-growth "cold spots." The Baltics are neither "hot" nor "cold" in terms of industry, while Bulgaria is a high-growth area. Poland is almost entirely within a FIRE "cold spot." The Baltics' growth cluster is cantered primarily around the Latvian capital of Riga. These results suggest that growth "clusters" are more likely to be located in the Baltics and the Balkans than in Central European nations such as Poland.

Perhaps, with arguably lower "starting points" in 1991 (the Baltics were part of the Soviet Union, and the Balkan nations joined the EU later than the 10 that joined in 2004), these countries are indeed growing faster. But these results indicate where—and in which industries—regional convergence is strongest. While evidence for overall convergence (region-wide, as well as aggregate), we do find interesting country-specific results.

Hegerty S.W. 2016. Regional Convergence and Growth Clusters in Central and Eastern Europe: An Examination of Sectoral-Level Data. *Eastern European Business and Economics Journal* **2(2)**: 95-110.

Conclusion

As Central and Eastern Europe continue their process of reintegration with the West, neoclassical growth theory suggests that individual regions should also converge with one another as those with low initial levels of per-capita GDP grow faster than regions with high initial levels. But, as previous studies show, convergence is more likely to occur at the national level than the regional level. This study tests this hypothesis, using spatial statistical methods, for 233 NUTS-3 regions and four individual sectors over the period from 2000 to 2013. These methods incorporate spatial weights in regression and "hot spot" analysis, testing for regional convergence and the presence of growth clusters.

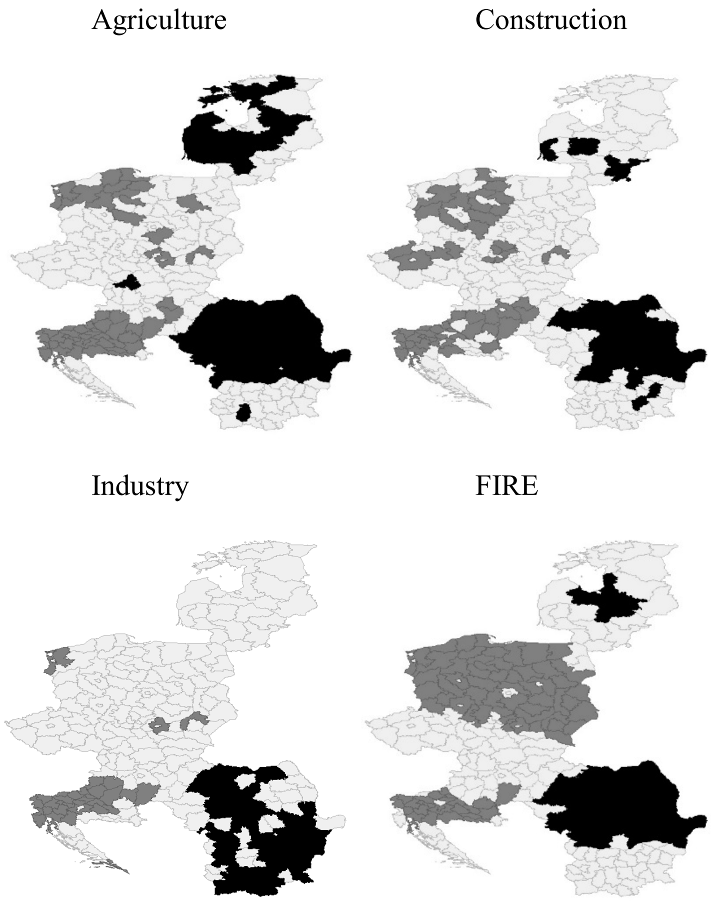


Fig. 4. Getis-Ord "Hot Spots" and "Cold Spots," Sectoral GVA Growth

A standard regression of GVA growth on initial levels finds no evidence for "beta convergence," except for in the construction sector for certain countries at the individual-nation level. Growth "hot spots" are found using the Getis-Ord G* statistic for aggregate GVA growth and sectoral growth for all sectors except industry in the Baltics and for all sectors in Bulgaria and Romania. Low-growth "cold spots" are located in Poland and Croatia.

Given these regional and sectoral differences policymakers should be wary of "one size fits all" growth policies in the CEE region. Instead, the specific strengths shown in the "hot spot" analysis could be nurtured to encourage further growth. It is also possible to use these findings to choose whether to disinvest from "cold spots" and invest in more promising sectors. On the other hand, further investment could be justified if there is sufficient will to create growth clusters where currently none exist.

Note: NUTS stands for "Nomenclature of Territorial Units for Statistics," with progressively smaller territorial units. NUTS-2 regions are fewer and larger than NUTS-3 regions.

References

Artelaris, P., Kallioras, D., & Petrakos, G. (2010). Regional inequalities and convergence clubs in the European Union new member-states. *Eastern Journal of European Studies*, **1(1)**, 1-13.

Azomahou, T.T., El Ouardighi, J., Nguyen-Van, P. & Pham, T.K.C. (2011). Testing convergence of European regions: A semiparametric approach. *Economic Modelling*, **28(3)**, 1202-1210.

Boldrin, M., Canova, F. Pischke, J.-S. & Puga, D. (2001). Inequality and convergence in Europe's regions: Reconsidering European regional policies. *Economic Policy*, **16(32)**, 205 and 207-253.

Chapman, S.A., Cosci, S., & Mirr, L. (2012). Income dynamics in an enlarged Europe: The role of capital regions. *The Annals of Regional Science*, **48(3)**, 663-693.

Corrado, L., Martin, R., & Weeks, M. (2005). Identifying and interpreting regional convergence clusters across Europe. *The Economic Journal*, **115(502)**, Conference Papers C133-C160.

Hegerty S.W. 2016. Regional Convergence and Growth Clusters in Central and Eastern Europe: An Examination of Sectoral-Level Data. *Eastern European Business and Economics Journal* **2(2)**: 95-110.

Dall'erba, S. (2005). Productivity convergence and spatial dependence among Spanish regions. *Journal of Geographical Systems*, **7**, 207–227.

Ezcurra, R. & Rapún, M., (2007). Regional dynamics and convergence profiles in the enlarged European Union: A Non-parametric approach. *Tijdschrift voor Economische en Sociale Geografie*, **98(5)**, 564–584.

Ezcurra, R. & Pascual, P. (2007). Spatial disparities in productivity in Central and Eastern Europe. *Eastern European Economics*, **45(3)**, 5-32.

Le Gallo, J. & Ertur, C. (2003). Exploratory spatial data analysis of the distribution of regional per capita GDP in Europe, 1980–1995. *Papers in Regional Science*, **82**, 175- 201.

Le Gallo, J. & Dall'erba, S. (2006). Evaluating the temporal and spatial heterogeneity of the European convergence process. 1980–1999, *Journal of Regional Science*, **46(2)**, 269 288.

Le Gallo, J., and Dall'erba, S. (2008). Spatial and sectoral productivity convergence between European regions. 1975–2000, *Papers in Regional Science*, **87(4)**, 505-525.

LeSage, J.P. (2014). What Regional scientists need to know about spatial econometrics. *The Review of Regional Studies*, **44(1)**, 13-32.

Mikulić, D., Lovrinčević, Ž., & Nagyszombaty, A.G. (2013). Regional convergence in the European Union, New Member States and Croatia. *South East European Journal of Economics and Business*, **8(1)**, 7-19.

Mora, T., Vayá, E. & Suriñach, J. (2004). The enlargement of the European Union and the spatial distribution of economic activity. *Eastern European Economics*, **42(5)**, 6-35.

Olejnik, A. (2008). Using the Spatial Autoregressively Distributed Lag Model in Assessing the Regional Convergence of Per-Capita income in the EU25. *Papers in Regional Science*, **87(3)**, 371-384.

Petrakos, G. (2001) Patterns of regional inequality in transition economies, *European Planning* Studies, **9(3)**, 359-383.

Petrakos G. & Economou D. (2002). The spatial aspects of development in Southeastern Europe. *Spatium*, **8**, 1-13.

Petrakos, G., Kallioras, D., & Anagnostou, A. (2011) Regional convergence and growth in europe: understanding patterns and determinants. *European Urban and Regional Studies*, **18(4)**, 375-391.

Sassi, M. (2010). OLS and GWR approaches to agricultural convergence in the EU-15. *International Advances in Economic Research*, **16**, 96–108.

Smętkowski, M. & Wójcik, P. (2012). Regional convergence in Central and Eastern European countries: A multidimensional approach. *European Planning Studies*, **20(6)**, 923-939

Tselios, V. (2009), Growth and convergence in Income Per Capita and income inequality in the regions of the EU. *Spatial Economic Analysis*, **4(3)**, 343-370.

Tsionas, E.G. (2000). Productivity Convergence in Europe, *Eastern Economic Journal*, **26(3)**, 297-320

Villaverde, J. & Maza, A. (2008). Productivity convergence in the European regions, 1980-2003: A sectoral and spatial approach. *Applied Economics*, **40**, 1299–1313.