REGIONAL DEVELOPMENT AND CRIMINALITY RATE IN ROMANIA: INSIGHTS FROM A SPATIAL ANALYSIS

Zizi GOSCHIN[1]

Abstract: *Although many recent studies have approached the topic of criminality, the regional dimension of the phenomenon is still under research. This paper employs a variety of statistical methods, from descriptive statistics to convergence and spatial econometrics, in an attempt to explore criminality rate in Romania, at county level, over 1990-2014. The analysis revealed that developed counties tend to have higher criminality rates, with Ilfov County and Bucharest Municipality frequently on top positions, and the county rankings are relatively stable in the short run. Against expectations, the regression models that have been estimated could not provide enough support for the GDP per capta (proxy for development level) as a statistically significant factor of influence on criminality rate in all years, but the explanatory variable "criminality rate in previous year" proved to be positive and highly significant in all models, indicating the relative inertia of this phenomenon.*

Keywords*: criminality rate; spatial model; county; Romania*

JEL Classification*: R10; R12; R58*

1. Introduction

Location-based analyses of criminal offences are highly popular since the development of sophisticated spatial analysis tools which are able to process geographically coded data. Such analyses help shed light on a wide range of social, economic or

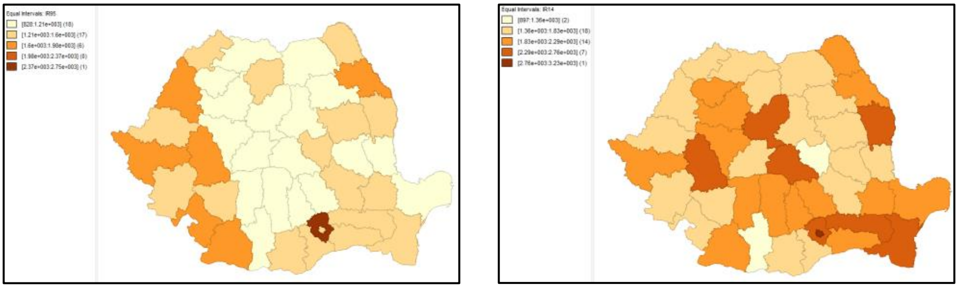
[1] *Bucharest University of Economic Studies, Romania, Institute of National Economy, Bucharest, Romania, e-mail:* zizi.goschin@csie.ase.ro

demographic factors that encourage/discourage crimes in a certain area (Sherman *et al*, 1989; Land *et al*., 1990; Levine, 1999; Messner *et al*., 1999, etc.).

Despite a big increase in the general criminality rate since the collapse of the socialism regime, Romania is still considered a safe destination, having a low overall crime rating (OSAC, 2015). The number of criminal offences largely varies throughout Romania, depending on demographic and socio-economic characteristics, big cities and densely populated areas being on the top of crime statistics.

Official statistics point to relevant regional differences in the overall criminality figures, the hot spots of crime changing in time. Figure 1 illustrates the territorial distribution of crime rates, revealing significant inequalities between Romanian counties, amid the overall rising trend in total criminal offenses per 100000 inhabitants during the period 1995 to 2014.

Figure 1: Spatial distribution of the criminality rates in Romania, in 1995 and 2014



(1995) (2014)

Source: author's processing using GeoDa software

In this context, we aim to explore the territorial variation of total infractions based on official data on criminality rate by county (NUTS 3 statistics). Criminality rate is measured as the number of definitive convicted people per 100,000 inhabitants. Official statistics on crime covers various offenses recorded by police, such as (attempted) intentional homicide, assault, kidnapping, sexual violence, robbery, burglary, motor vehicle theft, and other unlawful acts. This data does not cover a recording of all crimes, as certain crimes remain unreported. Fluctuations in the crime levels may be induced by methodological changes or improvements in crime reporting, such as the one in 15 June 2004, when the 112 emergency phone call service came into operation in Romania.

Despite significant regional variability in criminal offences, the issue of crime convergence has never been approached in the Romanian economic research. Real convergence is a topic of high interest in regional science, with most empirical studies addressing income and productivity convergence, but rarely crime-related topics. In this paper we contribute to this strand of literature by addressing the long-run trends in crime variability and inequalities from a territorial perspective and by assessing the convergence process with specific spatial analysis methods. Our research targets the interval 1990 to 2014, but, due to data limitations, the beta convergence model covers the period 1995 - 2014, further divided in three relevant sub-periods.

The rest of our paper is structured as follows. Section 2 describes the statistical methods employed in the empirical research, focusing on the beta convergence models in a spatial regression framework. Section 3 presents and discusses the results both from statistic and socio-economic perspectives and section 4 concludes by summarising the main findings.

2. Methods, variables and data

In this empirical research on criminality rate, we combine the traditional convergence analysis (sigma and beta convergence) with spatial regression models that account for likely spatial autocorrelation issues.

Starting with the seminal paper of Barro and Sala-i-Martin (1995) the sigma and beta convergence methods have been extensively used in regional studies in order to asses the scale and trend of territorial inequalities. The sigma convergence indicator measures the overall territorial variation:

$$\sigma = \frac{\sqrt{\frac{\sum_{i=1}^{n}(CR_i - \overline{CR})^2}{n}}}{\overline{CR}} \tag{1}$$

where CR_i is the criminality rate by county. Diminishing values of this indicator, in a certain period of time, indicate convergence. When the values of the indicator are growing in time, it means divergence.

The second method is beta convergence, based on the estimations of a regression model that explains the growth rate of a variable in relation to its initial regional levels. For instance, in the case of criminality rate, beta convergence occurs if the number of crimes growths faster in the regions having lower criminality levels at the beginning of the period.

The beta convergence model might be applied in two forms: absolute and conditional (Galor, 1996). In this paper we prefer to estimate conditional beta convergence models, as they allow us to include additional regressors that reflect the distinctive local characteristics.

We are going to estimate both classic and spatial beta convergence models. Our analysis starts with a classic OLS model of convergence:

$$\frac{1}{T}\ln\left(\frac{CR_{0+T,i}}{CR_{0,i}}\right) = a + b \cdot \ln CR\_initial_i + \sum_k c_k \ln X_{ki} + \varepsilon_i \tag{2}$$

Where: $\frac{1}{T}\ln\left(\frac{CR_{0+T,i}}{CR_{0,i}}\right)$ is the annual average growth in criminality rate in county i, $CR\_initial_i$ represents the criminality rate in county i at the beginning of the period, X_k are the additional explanatory variables (see Table 1) and ε stands for the error term.

We will further compute the Moran's *I* statistic (Anselin and Rey, 1991) and apply the permutations test to asses if there is spatial dependence in the counties' criminality rates.

Since spatial dependence (if present) negatively affects the regression estimations, we need to replace the classic model with a spatial one (Anselin, 2005; LeSage and Pace, 2009). We will firstly estimate the spatial lag specification:

$$\frac{1}{T}\ln\left(\frac{CR_{0+T,i}}{CR_{0,i}}\right) = a + b \cdot \ln CR\_initial_{,i} + \sum_k c_k \ln X_{k,0,i} + \rho \sum_j w_{ij} CR_{0,i,j} + \varepsilon_i \tag{3}$$

Where: $\sum_j w_{ij} CR_{0,i,j}$ is the spatial lag of the dependent variable and w_{ij} are the spatial weights that describe the regional structure of the country.

The second spatial specification to be tested in our paper is the spatial error model:

$$\frac{1}{T}\ln\left(\frac{CR_{0+T,i}}{CR_{0,i}}\right) = a + b \cdot \ln CR\_initial_i + \sum_k c_k \ln X_{ki} + \left(\lambda \sum_j w_{ij}\varepsilon_j + v_i\right), \tag{4}$$

where $\sum_j w_{ij}\varepsilon_j$ represent the spatially autoregressive errors and v_i the new uncorrelated errors of the spatial model.

The final choice of the best model for our data is based on the value of Lagrange multiplier test for both spatial error and spatial lag.

In our search for reliable regional predictors of criminality, we selected for the conditional beta convergence model the most relevant variables, as indicated by the international literature, but within the limits of official statistics currently available (Table 1).

Table 1. The variables

Variable name	Description	Data source
CR_growth	Annual average growth rate of criminality rate over the period of interest.	National Institute of Statistics and own computations
CR_initial	Criminality rate (total number of criminal offences per 100,000 inhabitants) at the beginning of the period of interest.	National Institute of Statistics and own computations
GDP/cap	Gross Domestic Product per inhabitant (Euro)	Eurostat database
FDI/cap	The foreign direct investments stock per capita (Euro)	The National Trade Register Office and own computations
Unempl	Unemployment rate (%)	National Institute of Statistics
Density	Population density (inhabitants per square km)	National Institute of Statistics
Divorce	The **divorce** rate per 1000 persons	National Institute of Statistics
Education	The share of tertiary educated per 1000 inhabitants	National Institute of Statistics and own computations

The international literature on criminality points to economic environment, demographics and law enforcement effectiveness as the most likely factors of influence (Blau, and Blau, 1982; Reiman, 2001; Harries, 2006). Romanian criminality also seems to be the larger in the developed regions, using GDP per inhabitant as proxy (Goschin, 2016).

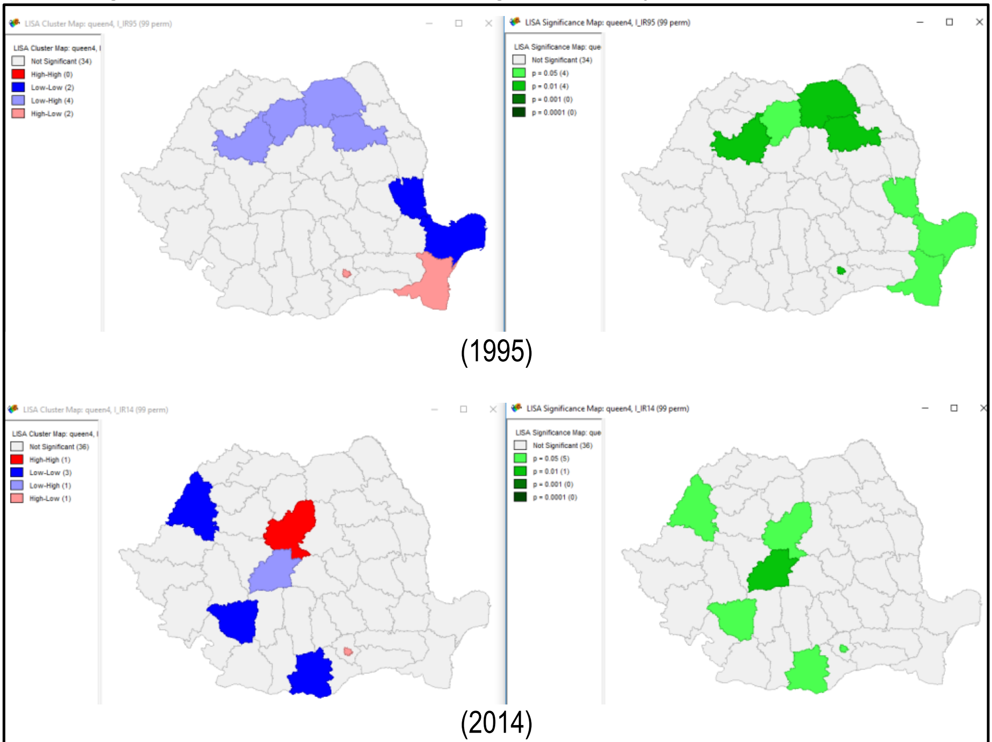
The divorce rate is largely considered in the literature as a significant predictor of criminality rate in a region, being extremely relevant especially for the level of adolescent delinquency (e.g. Burt et al., 2008). Criminality naturally rises with population density, as frequently documented in many empirical studies (e.g. Harries, 1995 and 2006; Li and Rainwater, 2000).

The data for our analysis came from several sources: the National Institute of Statistics, Eurostat database, The National Trade Register Office and own computations and covers the period 1990 to 2014.

3. Results and discussion

The territorial distribution of crime rates changes in time, indicating significant differences between Romanian counties (Figure 1). At the same time, there are some concentrations of counties with high or low criminality rates, or a combination of these (high crime locations surrounded by low crime locations or the opposite, a low-high mixture) as revealed by the maps displayed in Figure 2.

Figure 2: Spatial clusters of low/high criminality rates, 1995 and 2014

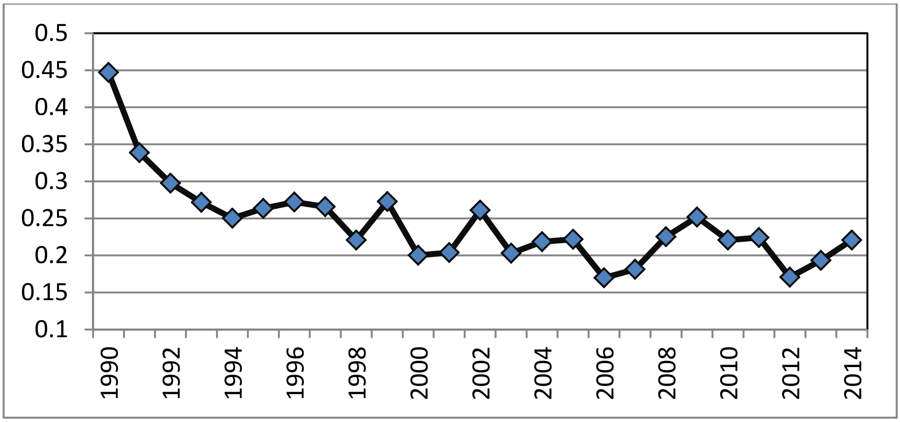


Source: author's processing in GeoDa.

Given the significant territorial variability in criminality rate in Romania and the general upwards trend in total number of crimes, we tested both sigma and beta convergence processes, to investigate a potential decline in crime inequalities among counties.

The computations based on relation (1) indicated a sigma convergence long-run trend in the criminal activity over the period 1990-2014 (Figure 3). This trend was stronger at the beginning of the period, then the sigma indicator started to fluctuate (convergence alternating with divergence) since 1997 and now seems to level.

Figure 3. Sigma convergence in crime



Source: author's processing

Although the territorial variation in criminality levels is now smaller, the total number of crimes is bigger. This means that the crime inequalities among Romanian counties declined in the context of generalized higher criminality rates.

We further tested the beta convergence hypothesis, using the regression specifications (2), (3) and (4). The results displayed in Table 2 show a significant beta convergence process for the overall period - 1995 to 2014 -, as well as for the three sub-periods that we analysed separately. All coefficients on initial criminality rates (CR_initial) are negative and highly significant, indicating that the average growth of criminality rate has been stronger in the counties having lower initial crimes. The consequence is a steady decline in criminality inequalities among Romanian counties, on the background of a step overall increase in total number of crimes.

As regards the factors that stimulated the overall rise in criminality, the regional development level (proxied by GDP per capita) and the population density are highly significant for the entire period investigated: 1995-2014. This is not a surprise, given the wealth of research on crime that pointed to similar factors (*e.g.* Blau and Blau,1982; Reiman, 2001). Depending on the period investigated, other significant factors of influence are the unemployment and divorce rates, which are positively linked to the regional growth in criminality rates, while FDIs and education have the opposite effect.

Population density seems to be a good predictor of regional criminality rates, given that it is significant in all investigated intervals, except for the transition period 1995-2000. Higher population density seems to stimulate criminal behavior by offering more opportunities, as documented in many empirical studies (*e.g.* Harries, 1995 and 2006; Li and Rainwater, 2000). The explanatory variables tested in the conditional beta convergence model seem to have their effects limited only to a certain interval (Table 2). The GDP per capita variable represents a special case, since it was highly significant over the entire period 1995-2014, but surprisingly not on the sub-intervals.

Table 2. The results for the beta convergence models (dependent variable – annual growth of criminality rate)

	1995-2014 Spatial error model**		1995-2000 Spatial error model**	
Variables	**Coefficient**	**Prob**	**Coefficient**	**Prob**
CONSTANT	-3.608	0.4348	0.817	0.0000
lnCR_initial	-0.050	0.0000	-0.095	0.0000
lnGDP/cap	0.050	0.0000		
lnUnempl	0.087	0.0008	0.037	0.0014
lnDensity	0.260	0.0604		
lnDivorce			0.051	0.0014
lnEducation			-0.007	0.0003
LAMBDA	0.969	0.0000	0.593	0.0000
Statistics	**Value**	**Prob**	**Value**	**Prob**
R-squared	0.8754		0.6472	
Log likelihood	157.134		93.217	
Breusch-Pagan test	1.0350	0.9045	0.9020	0.9247
Likelihood Ratio Test (spatial dependence)	338.231	0.0000	8.3460	0.0039
	2000-2008 Spatial error model**		**2008-2014 Classic model***	
Variables	**Coefficient**	**Prob**	**Coefficient**	**Prob**
CONSTANT	0.936	0.0000	0.982	0.0000
lnCR/cap initial	-0.133	0.0000	-0.144	0.0000
lnFDI/cap	-0.011	0.0001		
lnDensity	0.016	0.0025	0.023	0.0033
LAMBDA	0.6458	0.0000		
Statistics	**Value**	**Prob**	**Value**	**Prob**
R-squared	0.6166		0.5046	
Log likelihood	98.1987			
F-statistic			19.8601	0.0000
Breusch-Pagan test	2.5758	0.4617	6.676	0.0355
Koenker-Bassett test			3.3683	0.1856
Likelihood Ratio Test (spatial dependence)	8.7018	0.0032		

**OLS estimation*

*** Maximum likelihood estimation*

The Lagrange Multiplier tests indicated that the spatial models are more appropriate for our data than classic regression, except for the period 2008-2014 (Table 2). This outcome confirms the findings of many previous empirical studies on criminality that highlighted the relevance of location and the need to use appropriate tools of spatial analysis (*e.g.* Land *et al.,* 1990; Levine, 1999; Messner *et al*., 1999).

4. Conclusions

The regional convergence in criminality rates in Romania has been empirically confirmed in this paper, based on sigma and beta traditional methods. Moreover, the conditional beta convergence model was estimated both in classic and in spatial specifications, accounting for the spatial autocorrelation that exists in the territorial levels of criminality rate by explicitly including it in the regression models. The hypothesis of beta convergence holds for the period 1995-2014, as well as for three sub-periods included in our analysis, while sigma convergence has been revealed for the interval 1990 to 2014.

Allowing for additional factors of influence on the regional convergence process, in the framework of the conditional beta convergence model, we found that economic development, unemployment rate, population density and divorce rates are positively linked to regional growth in criminality rates, while FDIs and education have the opposite effect. These significant factors of influence highlighted by our research on regional criminality in Romania are in line with the international mainstream literature.

Since the statistic tests indicated that the spatial models are more appropriate for crime data than classic OLS regression, we emphasize the relevance of location in this area of research and the need to use specific tools of spatial analysis in studies on regional criminality.

Further research should confirm the robustness of these results and deepen the analysis by examining the distribution of different types of crimes.

References

Anselin, L. (2005), *Exploring Spatial Data with GeoDaTM : A Workbook*, Spatial Analysis Laboratory Department of Geography University of Illinois, Urbana, http://sal.agecon.uiuc .edu/

Anselin, L. and Rey, S. (1991) "Properties of Tests for Spatial Dependence in Linear Regression Models*", Geographical Analysis*, 23, pp. 112–131.

Barro, R.J. and Sala-i-Martin, X. (1995) *Economic Growth*, New York: McGraw-Hill.

Barro, R.J. and Sala-i-Martin, X. (2004) *Economic growth*, 2nd edition., MIT, Cambridge

Blau, J., & Blau, P. (1982) "The cost of inequality: Metropolitan structure and violent crime", *American Sociological Review*, 47 (1), 114–129.

Burt, S. A., Ashlee R. Barnes, Matt McGue, William G. Iacono (2008) “Parental Divorce and Adolescent Delinquency: Ruling out the Impact of Common Genes”, Developmental Psychology, 44(6): 1668–1677.

Galor, O. (1996) “Convergence? Inferences from Theoretical Models”*, Economic Journal*, Royal Economic Society, vol. 106(437), pp. 1056-1069

GeoDa (2014), The GeoDa Center for Geospatial Analysis and Computation , http://geodacenter.asu.edu/about

Goschin, Z. (2016), “Mapping global and economic crime in Romania. Regional trends and patterns”, *Romanian Journal of Economics*, vol. 42 (2) (forthcoming).

Harries K., (2006) “Property Crimes and Violence in United States: An Analysis of the influence of Population density”, *International Journal of Criminal Justice Sciences*, Vol 1 Issue 2

Harries, K., (1995). “The ecology of homicide and assault: Baltimore City and County, 1989-91”, *Studies in Crime and Crime Prevention* 4, 44-60.

Land, K., P. McCall, and L. Cohen. 1990. Structural covariates of homicide rates: Are there invariances across time and social space? , *American Journal of Sociology*, 95:922–963.

LeSage, J.P. (1999) *The Theory and Practice of Spatial Econometrics*. Department of Economics, University of Toledo.

LeSage, J.P., Pace R.K. (2009) *Introduction to Spatial Econometrics*, Boca Raton, CRC Press.

Levine, N. (1999) CrimeStat: A spatial statistics program for the analysis of crime incident locations.Washington, D.C.: U.S. Department of Justice, National Institute of Justice.

Li, J. and Rainwater, J. (2000) The real picture of land-use, density, and crime: A GIS application. Available at: http://gis.esri.com/library/userconf/proc00/professional/papers/PAP508/p508.htm

Messner, S., L. Anselin, R. Baller, D. Hawkins, G. Deane, Tolnay, S. (1999) The spatial patterning of county homicide rates: An application of exploratory spatial data analysis, *Journal of Quantitative Criminology*, 15 (4): 423–450.

National Institute of Statistics, Database TEMPO - time series https://statistici.insse.ro/shop/

OSAC (The Overseas Security Advisory Council), U.S. Department of State. Romania 2015 Crime and Safety Report, available at: https://www.osac.gov/pages/ContentReportDetails.aspx?cid=17288

Reiman, J. (2001) *The rich get richer and the poor get prison: Ideology, class, and criminal justice.* Boston: Allyn and Bacon.

Sherman, L.W., Gartin, P.R., Buerger, M.E. (1989) Hot spots of predatory crime: Routine activities and the criminology of place, *Criminology,* 27:27–55.