Local Factors Explaining the Incidence of Criminal Offences in Romania. A Geographically Weighted Regression Model

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ABSTRACT

Criminality has long became a matter of increasing concern for national and local decision makers alike, given the high disturbances, hardships and adversities it brings to the social and economic environment. In the last decades the number of criminal offences displayed growing territorial inequalities across Romania. The incidence of criminality in a region depends not only on local socioeconomic conditions, but also on the ones in nearby regions, due to significant population mobility. Spatial econometric techniques account for such territorial correlations, including the use of spatial weights that capture the influence of each region upon its neighbours. Among the spatial methods, the geographically weighted regression (GWR) is a valuable instrument that allows estimating local coefficients, specific to each location, thus providing useful information for appropriate policy design at regional level. In this context we employed a criminality GWR model in an attempt to find the local determinants, both economic and demographic, that explain the spatial distribution of criminal offences in Romania. The results indicated that the incidence of this phenomenon in Romania is linked to factors largely acknowledged in the literature, such as local development, incomes, unemployment, and population density. The novelty brought about by the GWR model compared to previous research is that it also revealed important spatial variations in the impacts of the variables and indicated which counties are more vulnerable to specific factors. From an econometric perspective the GWR model represents a better fit than the classic OLS model, in addition to capturing the spatial variation in coefficients' estimation.

Key Words: *criminality rate, geographically weighted regression, regions, Romania*

JEL Classification: *R19, C54.*

INTRODUCTION

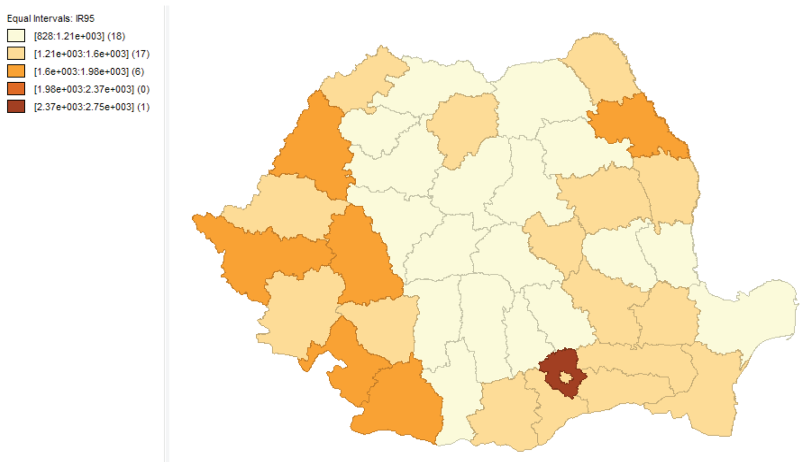
The disturbances, hardships and adversities entailed by criminal offences erode both social and economic environment and raise multiple challenges for the law-enforcing agencies aiming to protect public security.

Although the Romanian criminality rate is on a steady upwards trend for nearly three decades, the country is still considered a safe destination, having a low overall crime rating in the international context (The Overseas Security Advisory Council, 2015). The criminality figures aggregated at national level mask relevant regional differences, since the local intensity of criminality tends to be very different across counties, according to specific socio-economic local conditions, large overcrowded zones usually attracting higher violence.

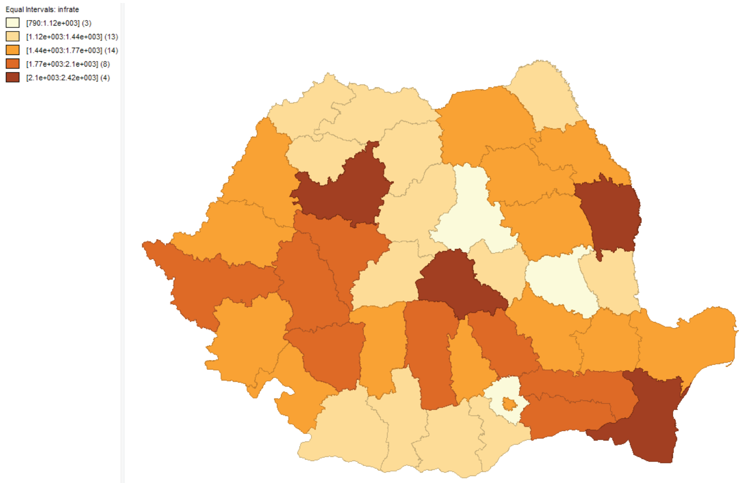
Official statistics reveal that the Romanian crime geography changes constantly, the inter-county differences systematically deepening since the 90th (Goschin, 2016a). The criminality maps in Figure 1 illustrate not only the overall increase in the number of criminal offences per 100,000 inhabitants between 1995 and 2015, but also the strong growth of spatial inequalities in this field.

Spatial Distribution of the Criminality Rates in Romania

Figure 1



(1995)



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Source: author's processing in GeoDa 1.6.7.

Given the existing regional diversity, it is unrealistic to expect uniform, equal impact of the factors of influence across the regions. The major crime determinants exert different local effects depending on specific characteristics and the statistic investigation tools need to adapt to the spatial heterogeneity of the data. Since classic global regression models cannot capture properly the important spatial variation of this phenomenon, we employed a geographically weighted regression (GWR) model to identify the local determinants of regional variations in criminality in Romania. The GWR model provides individual coefficient estimations for each region and indicates which counties are more vulnerable to specific factors, thus conveying useful information for shaping the appropriate anti-crime policies, depending on local specificities.

The remainder of this paper is organized as follows. The next section briefly reviews the literature, highlighting the main factors that determine the regional variations in the incidence of criminal offences. Section 3 outlines the methodological framework of the empirical analysis, namely the geographically weighted regression, pointing at its advantages compared to classic global regression. The main results of our empirical investigation on Romanian inter-county variations of criminality rate are illustrated in Section 4, where their policy implications are also considered. The last section concludes.

LITERATURE REVIEW

A wealth of criminality analyses undertaken in various countries highlighted multiple socioeconomic and demographic aspects that help to explain the incidence of criminal offences in connection to the specific socioeconomic and demographic conditions in a certain location. Among these factors, the most important are considered resource deprivation, socioeconomic inequalities, demographic characteristics, and rule of law enforcement (Blau, and Blau, 1982; Sherman et al., 1989; Land et al., 1990; Levine, 1999; Messner et al., 1999; Baller et al. 2001; Reiman, 2001; Harries, 2006; Deane et al., 2008, etc.).

Criminality naturally rises with population density, as frequently documented in many empirical studies (e.g. Harries, 1995 and 2006; Li and Rainwater, 2000). Overcrowded locations not only stimulate violence due to increased competition over limited resources, but also provide more opportunities for delinquency. Urbanisation, naturally associated with high population density, has the same effect (Messner et al., 2011).

A higher level of education tends to curb violence (Ingram, 2014), while economic inactivity, proxied by the unemployment rate prompts it (Messner et al., 2011). Family disruption, proxied by the divorce rate, is another criminality enhancer (Baller et al. 2001; Flores and Rodriguez-Oreggia, 2014), its relevance increasing in the case of adolescent delinquency (e.g. Burt et al., 2008).

Regional development level gives mixed effects, depending on the perspective. On one hand, rich regions account for higher criminality, especially when surrounded by poorer neighbourhoods. Romanian criminality also seems to be the larger in the developed regions, using GDP per inhabitant as proxy (Goschin, 2016a). On the other hand, at an individual level poverty might prompt criminal behaviour since lack of sufficient income increases the temptation to perform illegal activities (Flores and Rodriguez-Oreggia, 2014).

An important strand of literature addressed the close link between the traffic and use of drugs and the incidence of violent crimes, the analyses focusing especially on Latin America (e.g. Rodriguez-Oreggia and Flores, 2012; Ingram, 2014; Ingram and Marchesini da Costa, 2016).

Improvement in the capacity of law enforcement agents to counter the various forms of criminal activities is documented in the literature as an efficient way to rein in this phenomenon (Rodriguez-Oreggia and Flores, 2012).

The spatial nature of the factors related to criminality has been largely identified and accounted for in recent research (Baller et al. 2001; Deane et al.

2008; Ratcliffe, 2010; Sparks, 2011; Messner et al., 2011; Rey, 2012; Ingram and Marchesini da Costa, 2016). Not only high criminality in a region can spill over in surrounding regions, but local criminality might increase due to worsening socio-economic conditions in the neighbourhood criminality “hot spots”. Such spatial interactions are explained in the literature based on diffusion and contagion effects (Flores and Rodriguez-Oreggia, 2014).

In the same register, our previous research on this topic, found high spatial variation in Romanian criminality rates, largely depending on the level of development of the counties (Goschin, 2016a), despite a significant sigma and beta convergence trend that has marked the dynamics of this phenomenon over the last decades (Goschin, 2016b).

RESEARCH GOALS, METHOD AND DATA

This paper seeks to explain the main economic determinants of the number of criminal offences based on official data at county level (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 fails to capture all criminal offences, as many crimes remain unreported. Time variations in crime figures might be partly explained by methodological changes or even improvements in crime reporting. For instance the introduction of the 112 emergency phone call service in 2004 greatly improved the rapid notification of criminal offences in Romania and the number of reported crimes rose swiftly afterwards.

Researchers in regional economics constantly search for new and improved instruments to allow for a deeper understanding of the economic factors and processes that unfold in different locations. The main aim is to capture the characteristics, particularities and specificities of each region, thus enabling the design of appropriate economic policies.

Such a method, well adapted to the needs of regional research, is the geographically weighted regression (GWR) model (Brunsdon et al., 1996; Fotheringham and Brunsdon, 1999; Fotheringham et al., 2002; Wheeler and Tiefelsdorf, 2005). Unlike the usual regression models which estimate global coefficients that apply equally to all regions, this method provides coefficient estimations that change from one region to another, according to spatially defined weights. Consequently, GWR lets the model to fluctuate territorially, capturing the real spatial patterns and reaching a better image of spatial variation of the phenomenon of interest, compared to traditional global models. The GWR method had been already used for criminality analyses, for instance for investigating homicide in Brazil (Ingram and Marchesini da Costa, 2016).

The customary specification of the geographically weighted regression is as follows (Charlton and Fotheringham, 2009):

$$y_i(r) = \beta_{0i}(r) + \beta_{1i}(r)x_{1i} + \beta_{2i}(r)x_{2i} + \ldots + \beta_{ni}(r)x_{ni} \tag{1}$$

where the intercept and all coefficients are specific to each region r. The relative location of each region in the larger area is captured by geographic weights w_i.

The coefficients β_i of the previous model are:

$$\hat{\beta}(r) = (X^T W(r) X)^{-1} X^T W(r) y \tag{2}$$

where W(r) is the diagonal weights matrix specific for the region r, capturing its location in a larger area (country): $W(r) = diag[w_1(r),..., w_n(r)]$.

Each observation *j* is weighted based on its distance d_{ij} from location *i*, as follows: observations farther than a distance *b* previously selected based on Akaike information criterion have a weight of zero, observations at location *i* have a weight of one and observations closer than distance *b* are given the weight of $\left[1-\left(\frac{d_j}{b}\right)^2\right]^2$.

This weighting procedure allows only close neighbours (i.e. closer than the threshold distance b) to be accounted for while estimating the local coefficients of each territorial unit.

Our paper targets the relevant factors documented in the crime literature, for the case of the 41 Romanian counties plus the Bucharest Municipality and asses their influence using the most recent data, namely for the year 2015. To reach our goal we fit a GWR model aimed to capture the main economic and demographic determinants of criminality from a regional perspective, using the GWR4 software.

The variables included in the model are presented in Table 1.

The variables

Table 1

Variable name	Description	Data source
Criminality	Criminality rate measured as total number of criminal offences per 100,000 inhabitants	National Institute of Statistics and own computations
GDP	Gross Domestic Product per inhabitant (Euro)	Eurostat database
FDI	Foreign direct investment stocks per capita (Euro)	The National Trade Register Office and own computations
Unemployment	Unemployment rate (%)	National Institute of Statistics
Density	Population density represents the number of inhabitants per square km	National Institute of Statistics and own computations
Urbanisation	Urbanisation rate is calculated as the number of urban relative to rural population (%)	National Institute of Statistics and own computations
Gender ratio	The gender ratio is computed as female population relative to male population	National Institute of Statistics and own computations
Divorce	Number of divorces per 1000 inhabitants	National Institute of Statistics and own computations
Education	Share of tertiary educated persons per 1000 inhabitants	National Institute of Statistics and own computations

Based on the findings of empirical studies in the literature and our own theoretical considerations, and everything else being equal, we expect population density, urbanisation rate, divorce rate, and unemployment rate to correlate positively with criminality rate, while education and gender ratio should exert negative influences. As regards GDP per capita and FDIs per capita, standard measures of development and economic growth, in a spatial perspective they are expected to be in a direct relationship with the criminality rate in the sense that wealth increases the opportunity for criminal offences and attracts both local perpetrators and the ones from surrounding communities.

The data for our analysis came from several sources: the National Institute of Statistics, Eurostat database, and The National Trade Register Office. All variables refer to the year 2015, as the latest available official statistics, and in order to achieve higher territorial comparability they have been rescaled (where appropriate) in per capita, per 1000 or per 100,000 inhabitants form.

EMPIRICAL RESULTS

In this paper we applied a GWR regression, using a Gaussian Model with an adaptive bi-square geographic kernel. We applied standardisation of independent variables, made use of the Golden section search method for optimal bandwidth and Akaike Criterion guided the optimal bandwidth selection. The number of nearest neighbours in the GWR model is 5.

The Adjusted R-squared and Akaike criterion provided by the output (Table 2) clearly show that GWR is an improvement to the global OLS regression.

The results from the GWR model

Table 2

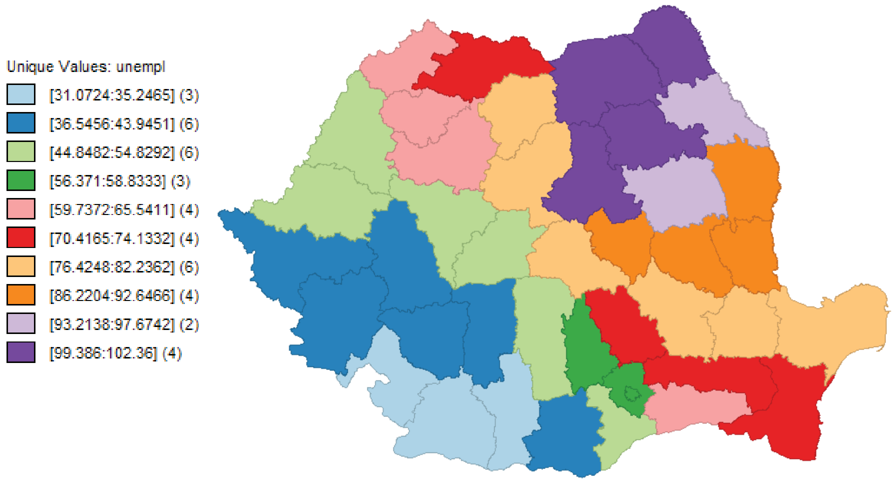
Variable	Minimum	Lower Quartile	Mean	OLS global coefficient (t statistic)	Upper Quartile	Maximum
0	*1*	*2*	*3*	*4*	*5*	*6*
Intercept	-2221.14	357.04	2095.118	4154.592 (1.228)	4146.34	5994.20
Unemployment	31.072	46.888	63.653	57.323** (2.250)	83.232	102.361
GDP	0.3347	0.6871	0.9989	1.1021** (2.898)	1.4158	1.8074
Urbanization	1266.104	1473.860	1621.194	1691.342*** (3.154)	1862.99	1983.08
Akaike AIC			608.045	613.385		
Adjusted R-squared			0.4854	0.3554		

From the list of the possible explanatory variables in Table 1 only urbanization, unemployment and GDP per capita proved to be significant and remained in the final specification of the GWR model.

The local coefficient estimations of each variable, as presented in Appendix, display large variability, against the constant OLS global estimation in Table 2, column 4. This reinforces the utility of the GWR model that is able to capture such local specificities. Thus, the local estimations for the variable unemployment rate range from a minimum of 31.072 in Dolj county to a maximum of 102.359 in Suceava county, while the global OLS model provides only the constant value of 57.322 (Table 2). The complete range of local values taken by the unemployment rate coefficients is displayed in Figure 2.

Local coefficient estimations for unemployment rate

Figure 2



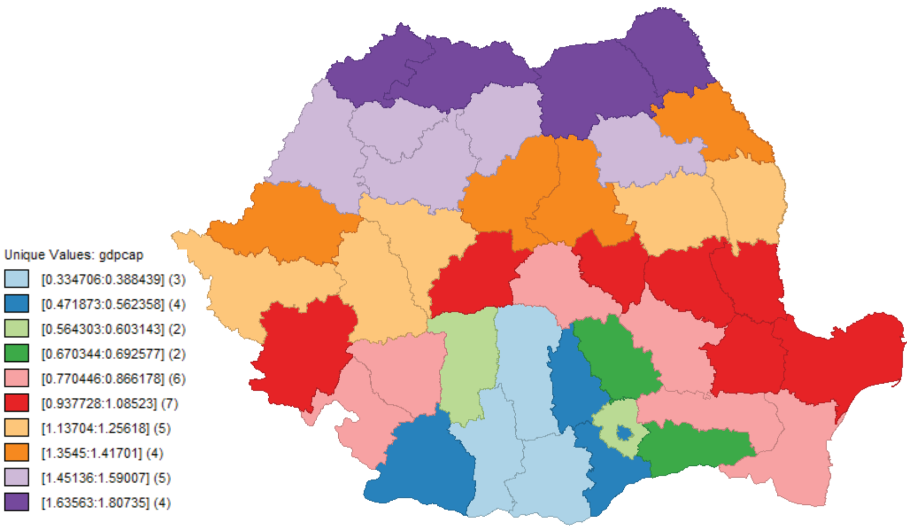
Source: author's processing in GeoDa 1.6.7.

The highest values of the local coefficients for the unemployment rate are recorded in North-East, where its criminality-enhancing effect is maximum, while the lowest values correspond to the West and South-East counties.

Local coefficient estimations for GDP per capita range from 0.3347 in Teleorman County to 1.8074 in Suceava County (Figure 3). As illustrated by the maps in Figure 3, the intensity of this factor of influence seems to fade in Romania from North to South.

Local coefficient estimations for GDP per capita

Figure 3

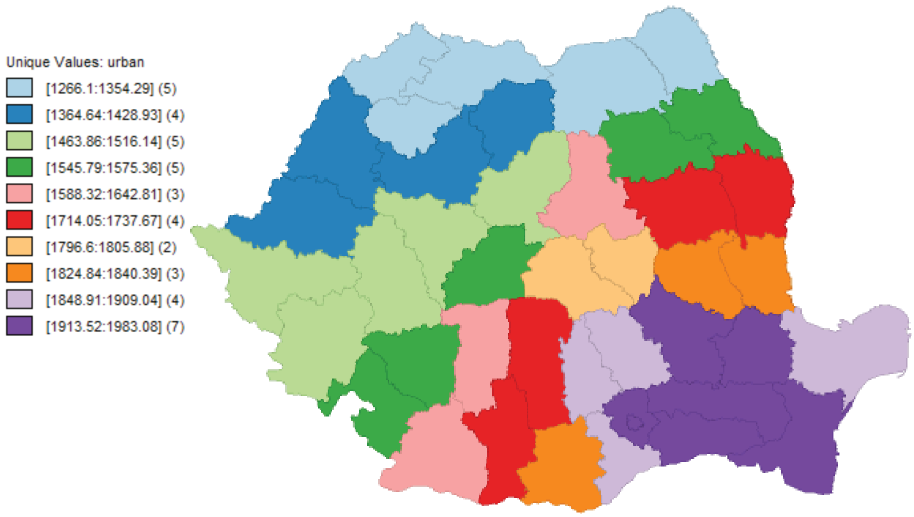


Source: author's processing in GeoDa 1.6.7.

Local coefficient estimations for the urbanisation rate range from 1266.104 in Suceava County to 1983.08 in Constanta County (Figure 4). This seems to be the strongest predictor of the incidence of criminal offences in Romania. Our results are in line with international studies indicating the high relevance of urbanisation for violent crimes, as for instance the study in Messner et al. (2011).

Local coefficient estimations for urbanisation rate

Figure 4

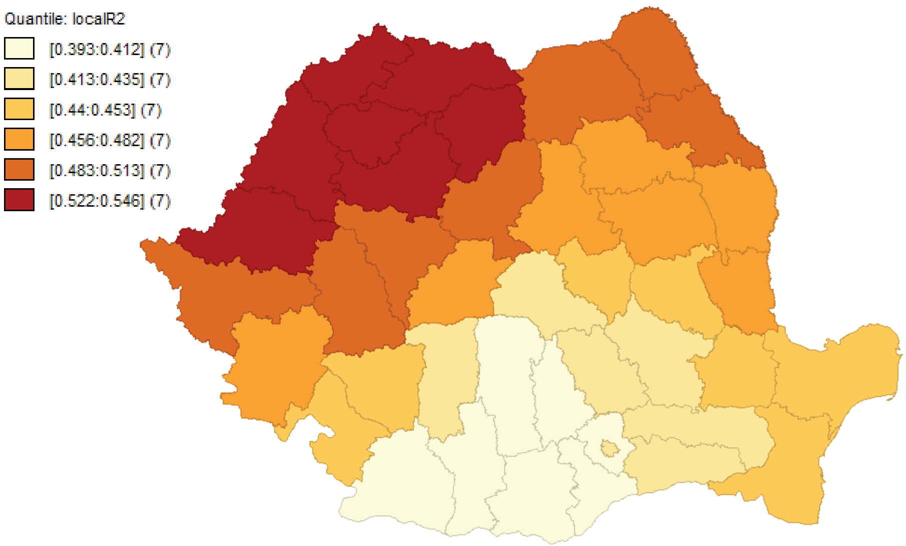


Source: author's processing in GeoDa 1.6.7.

The local coefficients of determination range between 0.393 and 0.546, indicating that all local regressions fit our data well, with highest values corresponding to North-West, and lowest values clustered in South (Figure 5).

The coefficient of determination (R-squared) by county

Figure 5



Source: author's processing in GeoDa 1.6.7.

In sum, the local coefficient estimations of every independent variable display significant variation across the Romanian counties, providing specific information for each location. The big territorial variability of the local estimations proves that GWR model is the right choice for our data.

CONCLUSION

Given that local anti-criminality policy faces the challenge of accounting for influences that cross the regional boundaries, spatial econometrics represent appropriate investigation tool for investigating this phenomenon. In this register, our paper employed a criminality GWR model in an attempt to find the local determinants, both economic and demographic, that can explain the highly unbalanced spatial distribution of criminal offences in Romania.

The results indicated that the incidence of criminal offences in Romania is linked to several factors largely acknowledged in the literature, such as local development, unemployment, and population density. The novelty brought about by our GWR model is that it also revealed important spatial variations in the local impacts of these variables and indicated which counties are more vulnerable to specific factors. The local estimates for each explanatory variable share the same sign, but differ greatly in magnitude and statistic significance from one county to another, depending on specific local conditions.

From an econometric perspective the GWR model represents a better fit than the classic OLS model, besides capturing the spatial variation in coefficients' estimation. The county-specific estimates provided by the GWR model represent useful information for shaping appropriate anti-crime policies, especially tailored to address properly the local specificities. By placing criminal offences in a proper geographic context and by applying appropriate spatial statistical analysis tools, we can better understand where and why crime activity is occurring and law enforcement agencies can respond more effectively.

Future research should target more detailed analysis by examining the spatial distribution and determinants of different types of crimes, given that there is a large variety of criminal offences and the factors of influence are likely to be different from one category to another.

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APPENDIX

Local coefficient estimations based on GWR model

County	Unemployment rate		GDP per capita		Urbanisation rate		Local R^2
	coefficients	t stat	coefficients	t stat	coefficients	t stat	
Alba	51.668	1.871	1.244	2.006	1477.196	2.513	0.501
Arad	44.848	1.564	1.355	2.078	1428.927	2.344	0.522
Arges	47.569	1.487	0.388	0.600	1737.669	3.029	0.396
Bacau	93.214	2.933	1.217	2.044	1721.107	2.958	0.464
Bihor	51.536	1.813	1.498	2.290	1368.273	2.208	0.537
Bistrita-Nasaud	79.039	2.706	1.590	2.512	1364.638	2.240	0.524
Botosani	100.915	2.786	1.688	2.470	1329.492	2.040	0.502
Braila	80.034	2.537	0.938	1.520	1920.699	3.185	0.444
Brasov	80.209	2.560	0.810	1.258	1796.603	3.063	0.432
Buzau	78.537	2.516	0.866	1.420	1913.517	3.254	0.435
Calarasi	65.541	2.057	0.693	1.113	1966.538	3.303	0.426
Caras-Severin	37.270	1.259	1.063	1.638	1516.141	2.546	0.482
Cluj	59.751	2.158	1.452	2.311	1400.311	2.328	0.524
Constanta	73.876	2.272	0.840	1.318	1983.084	3.185	0.440
Covasna	87.389	2.859	1.011	1.685	1805.881	3.144	0.444
Dambovita	56.371	1.769	0.472	0.759	1848.913	3.250	0.401
Dolj	31.072	0.994	0.487	0.778	1642.814	2.865	0.411
Galati	86.898	2.761	1.085	1.796	1836.664	3.091	0.456
Giurgiu	51.425	1.607	0.483	0.785	1905.244	3.316	0.407
Gorj	36.546	1.221	0.796	1.244	1574.197	2.698	0.446
Harghita	100.189	3.065	1.415	2.237	1588.321	2.638	0.480
Hunedoara	43.945	1.547	1.137	1.803	1501.899	2.550	0.491
Ialomita	72.534	2.260	0.788	1.256	1967.821	3.252	0.432
Iasi	97.674	2.888	1.417	2.310	1565.408	2.607	0.483
Ilfov	58.833	1.856	0.564	0.918	1919.067	3.329	0.412
Maramures	74.133	2.532	1.666	2.562	1301.974	2.081	0.538
Mehedinti	31.945	1.032	0.770	1.178	1568.364	2.655	0.443
Municipiul Bucuresti	58.309	1.838	0.562	0.915	1921.914	3.330	0.413
Mures	76.425	2.747	1.377	2.280	1490.887	2.554	0.500
Neamt	99.386	2.947	1.451	2.316	1545.794	2.567	0.482
Olt	35.246	1.116	0.372	0.599	1714.052	3.023	0.397
Prahova	70.417	2.225	0.670	1.085	1909.039	3.299	0.416
Salaj	59.737	2.127	1.542	2.399	1354.293	2.202	0.536
Satu Mare	62.698	2.195	1.636	2.495	1305.791	2.076	0.546
Sibiu	54.829	2.003	1.011	1.666	1575.356	2.751	0.469
Suceava	102.360	2.822	1.807	2.542	1266.105	1.896	0.513
Teleorman	40.786	1.246	0.335	0.538	1824.839	3.200	0.393
Timis	40.694	1.396	1.256	1.919	1463.859	2.416	0.510
Tulcea	82.236	2.578	1.012	1.625	1906.679	3.100	0.453
Valcea	39.403	1.297	0.603	0.937	1625.278	2.809	0.422
Vaslui	92.647	2.871	1.237	2.063	1724.603	2.918	0.469
Vrancea	86.220	2.778	1.040	1.739	1840.390	3.151	0.450

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