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The economic consequences of crime in Italy

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Abstract

Purpose – The purpose of this paper is to employ provincial data to study the relationship between several crime typologies, namely murder, robbery, extortion and fraud and economic output in Italy.
Design/methodology/approach – The authors propose a spatial econometric approach where the spatial proximity is defined by a measure of physical distance between locations, in order to take into account possible spill-over effects.
Findings – The results of the spatial estimation suggest that criminal activities, namely murder and robbery, exhibit a negative impact on Italian gross domestic product while fraud and total crime do not affect economic output and that there are beneficial spill-overs from neighbouring provinces.
Originality/value – The study empirically shows that only violent crimes have a crowding-out effect on economic output.

Keywords Italy, Tourism, Crime, Crowding-out effect, Spatial models, Spatial weights
Paper type Research paper

1. Introduction

Crime is an important social phenomenon that directly and indirectly affects our daily life. This is not only because criminals produce or offer goods and services that otherwise would not be available, but also because illegal activities have an impact on our lifestyle. They affect where we live and go on holiday, what we do at the weekend in our free time, and so on. Given the importance of crime, the relationship between economic performance and criminal activity both at macro and micro level has become an important field of study in recent decades.

According to Field (1990), a bidirectional causal effect can be observed. On the one hand, economic fluctuations have an impact on crime rates through two different types of incentive (Cantor and Land, 1985): motivation effects and opportunity effects. The former refers to the incentive to commit crime due to bad economic conditions; i.e. during recessions individuals increase their criminal activities to raise their income. The latter works in the opposite way; during recessions the reduction in the availability of goods decreases the opportunities to commit crime. Depending on the relative importance of the two components (motivation effect and opportunity effect), different crime types can display pro-cyclical or counter-cyclical behaviour with respect to business cycles, as was shown by Detotto and Otranto (2012) in the case of Italy.

On the other hand, Field (1990) indicated that crime affects economic growth in different ways. Criminals reallocate resources among agents, creating uncertainty and inefficiency. Crime also diverts resources from legal activities to illegal ones, reducing investments and consumption. In this sense, crime acts like a tax although such "overhead expenditures" are just for private benefits and not for public ones (Hillman and Schnytzer, 1986). For this reason, Tullock (1967) argues that goods and money stolen in property crimes cannot be considered as social costs since they are just pure (forced) transfers from one individual to another. However, welfare costs arise from

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both the opportunity costs of agents employed in criminal activities and in combating crime (Tullock, 1967) and the intangible victim costs due to pain, suffering and reduced quality of life (Cohen, 2000).

This analysis contributes to the latter strand of empirical research by studying the impact of crime on gross domestic product (GDP) in a sample of 103 Italian provinces. Studies on the crime-GDP relationship in Italy are dominated by time-series techniques (Detotto and Otranto, 2010; Detotto and Pulina, 2013). Clearly, these approaches do not allow possible geographical effects to be investigated. A recent exception is the work by Daniele and Marani (2011) in which they employ a panel data analysis to examine the impact of several types of crime, those traditionally connected to criminal organisations, on direct foreign investment inflows in the Italian provinces.

To the best of our knowledge, the present work is the first attempt to use Italian provincial data, taking into account potential geographical spillover effects, to gauge the impact of criminal activity on economic performance. A visual analysis shows that there are geographical clusters, which are related to both criminal activity and per capita income. This means that the legal and illegal activities in a given location may depend on the same activities in neighbouring areas. The reason for this is that spatial spillover effects are unobserved, but these may affect the economic behaviour of units in a given area.

This may mean that a spatial analysis framework is necessary, in order to check for possible geographical interaction between any neighbouring provincial pair. Many empirical works do not consider spatial autocorrelation. However, if the spatial correlation is due to the direct influence of neighbouring administrative units, the OLS estimate is biased and inefficient. The spatial econometric framework used in this work attempts to deal with this problem.

Total crime index measures the aggregate level of criminal activity in a province; it roughly represents a synthetic level of criminal activity. The expected sign of the correlation between total crime offences and GDP per capita is not obvious. On the one hand, we can expect that richer regions exhibit higher level of illicit activities since they attract criminal agents. In other words, the incentive to commit crime offences is high due to better economic conditions. In this framework, a positive correlation between crime and economic output is expected. On the other hand, as highlighted by Mauro and Carmeci (2007), criminal activities could become self-reinforcing causing a persistence of bad economic condition. Form this point of view, crime can induce a poverty trap in which the economy may end up in two different equilibria: the first is characterised by high crime and low production, the second by high income with low crime rates (Mehlum *et al.*, 2005; Mehlum *et al.*, 2006). In this latter case the correlation is expected to be negative.

Historically, illicit Italian activity consists mainly of property crimes, like fraud, extortion and robbery, in which the economic motivations of the criminals play a significant role (Detotto and Pulina, 2013). Our expectation is that such crime typologies can reduce consumption and investments since reallocating resources from legal to illegal activities they increase economic agents' uncertainty. Finally, murder is used since it can be considered as a proxy of the level of violence in a given region. The rationale is that violent crime reduces the willingness of individuals and firms to invest in areas within the country that are perceived to be unsafe.

Since the official crime data generally comes from the police, it is well known that the figures under report the real situation and suffer from under-recording bias (Mauro and Carmeci, 2007). This means that they represent only the tip of the iceberg.

Following Forni and Paba (2000), Mauro and Carmeci (2007) and Detotto and Otranto (2010), we could take the number of homicides as a proxy for general criminal activity. The homicide rates are the most reliable of all crime variables and, especially in hot spots of Mafia or other similar illicit activities, they may provide a rough indicator of organised crime.

Our cross-section analysis descends directly from the standard growth model à la Barro (1991) in which the economic output, namely GDP per capita, is regressed on a set of covariates representing labour and capital variables which are expected to be correlated with. Then, a crime index is also included in order to check whether illicit activities play a role in determining GDP differences.

Since the presence of spatial dependence leads to unbiased but inefficient ordinary least squares (OLS) coefficients (Anselin, 1988) due to the non-diagonal structure of the disturbance term, we use two spatial econometric approaches: the spatial error model (SEM) and the spatial lag model (SLM). Precisely, the former allows for the spatial autoregressive components whole the latter models the autoregressive disturbances structure. Then, a spatial autoregressive model with autoregressive disturbances (SARAR), in which the two components are simultaneously estimated, is also proposed (Anselin and Florax, 1995). Physical proximity is defined as the Euclidean distance between each possible pair of locations, according to their geographical coordinates. The spatial influence on location i corresponds to the weighted sum of the variable of interest in each location j, where the weights are given by the inverse distance between i and j.

The results of the spatial estimation suggest that crime negatively impacts GDP. To be more precise, total crimes, frauds and extortions do not seem to affect economic output, while the effects of murders and robberies are statistically significant. In other words, an increase in the murder and robbery rate by 1 per cent reduces economic output by 0.037 and 0.033 per cent, respectively. Our findings also indicate that there are positive spill-over effects among the Italian provinces. We find that an increase in the average level of GDP among neighbouring provinces leads, on average, to an increase of 0.623 in the GDP of a given province.

Since such results could be affected by endogeneity problems, due to the bi-directional causal relationship between legal and illegal activities (as shown by Field, 1990) and thus lead to biased estimates, an instrumental variable approach is proposed. According to Anselin (1988), each crime index is instrumented by using its spatial lagged representation. The motivation is that an economic shock in a given province probably affects local criminal activities but it does not impact the average level of crime rate in the neighbouring provinces. To be more precise, our conjecture in the case under investigation is that a variation of GDP in a given province has a negligible effect on the average crime rate in the related group. Such instrument variables approach is used in order to check for the endogeneity of crime index by employing a version of the Hausman test proposed by Davidson and MacKinnon (1989, 1993).

The article is organised as follows. Section 2 gives a brief overview of recent works on crime impacts on economy. Then, Section 3 provides a description of the data set and the variables used. Section 4 describes the theory underlying the spatial regression models. Section 5 presents results and comments. Section 6 concludes.

2. Literature review

Crime causes huge social and economic costs for society, as it has been demonstrated in several empirical studies until now. Traditionally, empirical research investigating the relationship between crime and economic performance has focused on terrorism and corruption, since it was commonly believed that these types of crime were the main reasons behind such a relationship. Only recently have other types of crime been taken into consideration.

For instance, Mauro (1995) showed that in 70 countries there was a significant negative relationship between "subjective corruption indices" and the growth rate in the early 1980s. Del Monte and Papagni (2001) estimated the negative effect of corruption on the productivity of expenditure on public investment employing a dynamic panel data approach at Italian regional level. Pellegrini and Gerlagh (2004) found that corruption affects economic growth by reducing the ratio of investment to GDP, as well as the country's openness. Interestingly, Mendez and Sepulveda (2006) showed empirical evidence of a non-linear relationship between corruption and income growth in the extent that corruption is "beneficial for economic growth at low levels of incidence and detrimental at high levels of incidence". Within a dynamic panel data framework, Freckleton *et al.* (2012) find that lower levels of corruption reduce the impact of FDI on economic growth, especially among developing economies.

Gaibulloev and Sandler (2008) measured the impact of domestic and transnational terrorism on per capita income growth for 1971-2004 for a panel of 18 western Europe countries.

In a time-series framework, Detotto and Otranto (2010) applied a time-varying coefficient approach to the Italian case and observed that crime negatively affects GDP growth and that its impact is higher during recessions than during economic expansions. By employing an autoregressive distributed lags approach, Detotto and Pulina (2013) investigate the bidirectional interrelationships between crime, employment and economic growth in Italy. Notably, all crime typologies, namely thefts, attempted or intentionally committed homicides, robberies, extortions, kidnappings, property crimes and total number of recorded crimes, have a negative effect on the employment rate. Furthermore, homicide, robbery, extortion and kidnapping negatively impact on economic growth.

Employing a panel-data approach, Peri (2004) measured the impact of murders on the annual per capita income growth in Italy, checking for a set of explanatory variables. Daniele and Marani (2011) used a panel data approach to measure the impact of crime on the inflow of foreign direct investment in 103 Italian provinces during the period 2002-2006. Using a spatial model at state level in Mexico, Pan *et al.* (2012) found that growth in real per capita GDP was negatively correlated to crime in neighbouring states, and positively related to crime within the state in the previous year. Then, Goulas and Zervoyianni (2013) used a panel of 25 countries over the period 1991 -2007 and found that crime has an asymmetrically negative effect on economic growth, and this impact is positively correlated with the degree of macroeconomic uncertainty.

More recently, Ashby and Ramos (2013) estimated the negative impact of organised crimes on net foreign direct investment from 116 countries into the 32 Mexican states from 2004 to 2010. Surprisingly, they found that crime negatively affected foreign investment in financial services, commerce and agriculture and encouraged oil and mining sectors, while there was no empirical evidence on the relationship between crime and foreign investment in manufacturing.

From this literature review it emerges that the causal relationship from crime to economic variables, such as GDP and unemployment, is an expanding field of research, within time series and cross-sectional frameworks. In light of existing literature, this paper aims to measure the impact of crime on income using Italian province data taking into account spatial spillover effects.

3. Description of the data

In this study we propose using the following model to explore the relationship between per capita GDP for 103 Italian provinces and a set of physical and non-physical determinants, together with a crime indicator:

$$LnGDP_i = \beta_0 + \beta_1 LnCRIME_{\mathrm{i}} + \beta_2 LnEMPLOY_{\mathrm{i}} + \beta_3 LnINFRA_{\mathrm{i}} + \beta_4 LnPATENT_{\mathrm{i}} + \beta_5 LnTOURISM_{\mathrm{i}} + \varepsilon_i \quad (1)$$

where ε_i is the error term. All the variables are transformed in a natural logarithmic specification (*Ln*) in order to reduce skewness values and assuming the existence of a non-linear relationship. $LnGDP_t$ is the natural logarithm of the income per capita in the *i*th province in 2009. Figure 1 clearly shows the asymmetric Italian income distribution in which the Northern provinces represent the richest part of the country.

LnCRIME measures the natural logarithm of the number of offences per 100,000 inhabitants in 2008. Five crime typologies are tested: total crime, robbery, extortion, fraud and murder. The correlation coefficients among all criminal typologies are shown in Table I. Notably, we observe that the correlation among all property crimes (robbery, fraud and extortion) is quite high (p-values > 0.99). Then, total crime is highly correlated with robbery and fraud, while murder with all property crimes. As shown in Figure 2, the Northern part of Italy presents higher levels of total crime than the Southern part of the country. For what concerns murder (Figure 3) and extortion (Figure 4), we can observe high crime rates in the South and in the big cities of Italy, like Geneva and Bologna. Notably, robberies and frauds are equally distributed within the national territory as displayed by Figures 5 and 6, respectively.

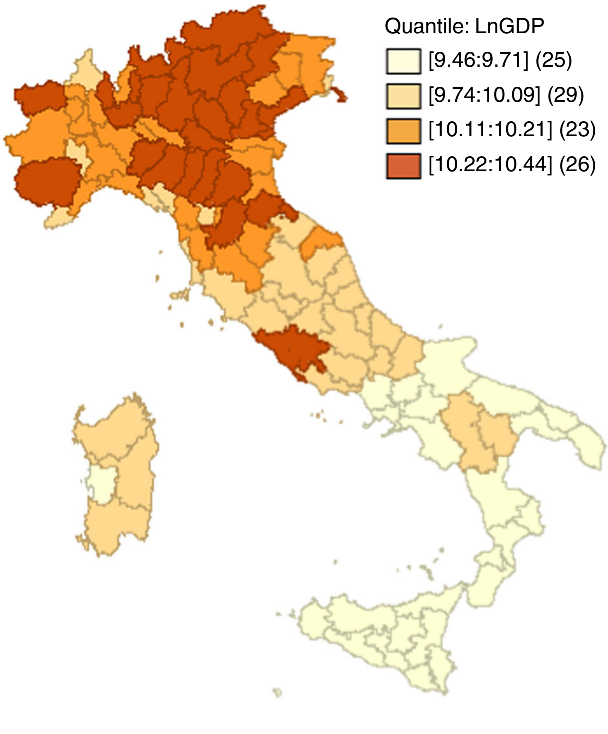

Figure 1.
GDP per capita in Italy (logarithm term)

$LnEMPLOY_i$ represents the natural logarithm of the employment rate in the *ith* province in 2008. It takes into account labour factor in explaining regional differences in Italian GDP. The expected sign is positive since historically a positive correlation is observed between employment rate and income.

$LnINFRA_i$ indicates the natural logarithm of the level of infrastructure in a given province in 2008, which values are in range between 23.3 (Nuoro, Sardinia) and 251.8 (Trieste, Friuli-Venezia Giulia). As shown by Aschauer (1989), the stock of public infrastructure capital is a significant determinant of aggregate total factor productivity. Canning (1999) and Demetriades and Mamuneas (2000) find a significant positive relationship between output and infrastructure in a cross-country panel data context.

	TOT_CRIME	MURDER	ROBBERY	FRAUD	EXTORTION
TOT_CRIME	1.0000				
MURDER	0.098	1.0000			
ROBBERY	0.685***	0.215**	1.0000		
FRAUD	0.505***	0.183*	0.444***	1.0000	
EXTORTION	0.152	0.322***	0.463***	0.371***	1.0000

Notes: (number of observations: 103). *,**,***Significance at the 10, 5 and 1 per cent, respectively

Table I. Correlation coefficients among crime typologies in logarithm terms: one-tailed Pearson test

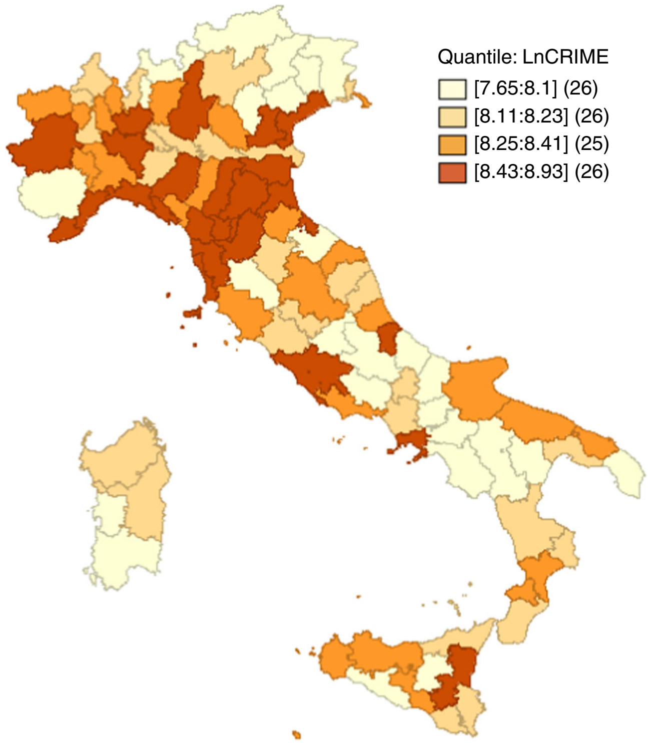

Figure 2. Number of total crimes per 100,000 inhabitants in Italy (logarithm term)

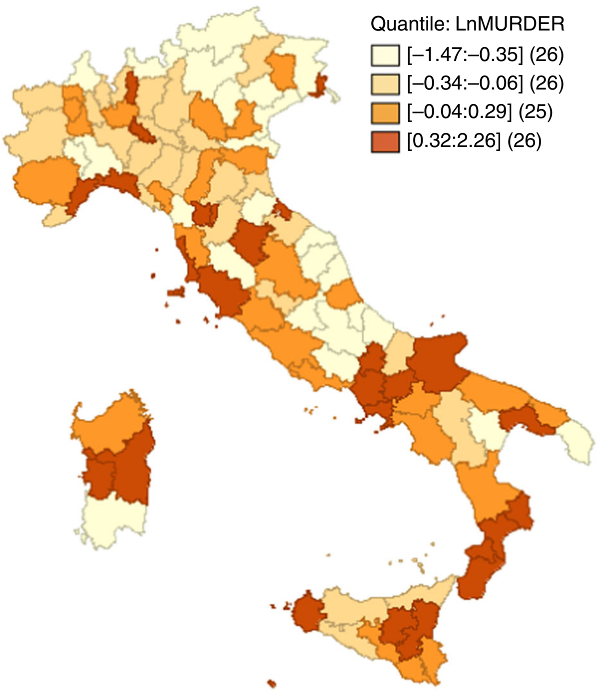

Figure 3.
Number of murders per 100,000 inhabitants in Italy (logarithm term)

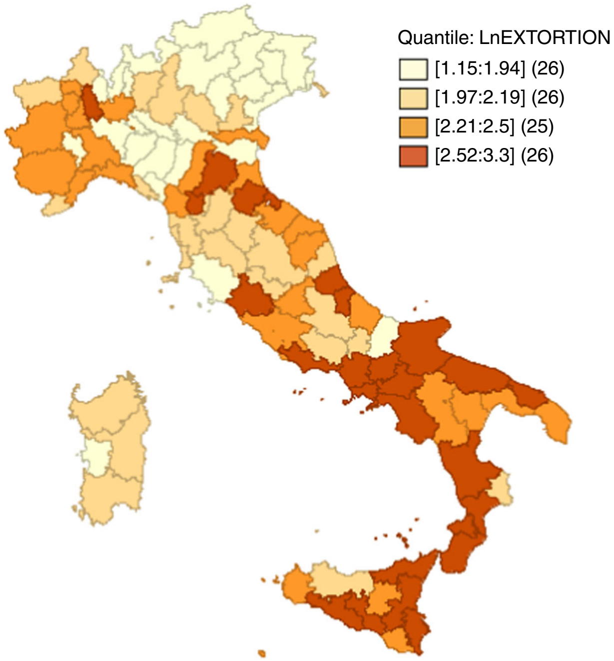

Figure 4.
Number of extortions per 100,000 inhabitants in Italy (logarithm term)

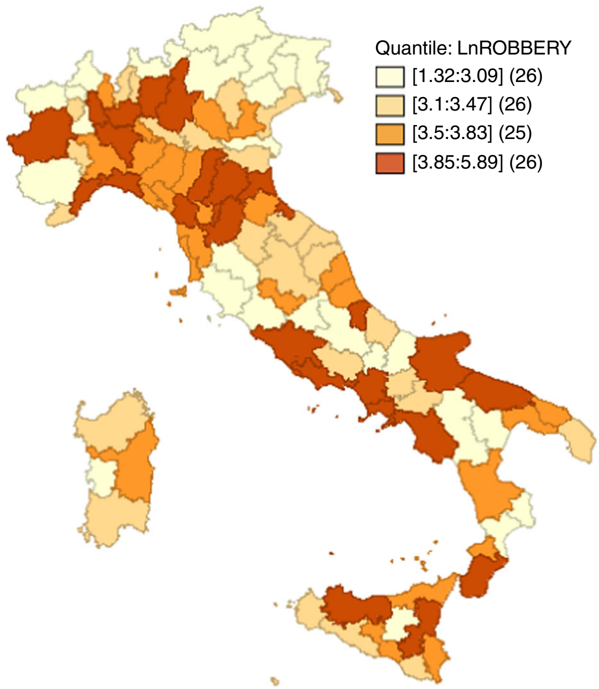

Figure 5.
Number of robberies per 100,000 inhabitants in Italy (logarithm term)

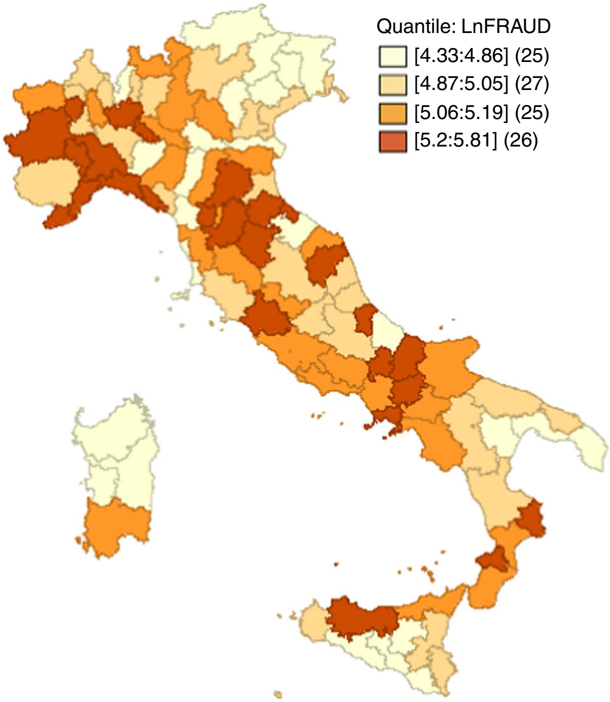

Figure 6.
Number of frauds per 100,000 inhabitants in Italy (logarithm term)

$LnPATENT_i$ measures the natural logarithm of the number of patents per 100,000 inhabitants in 2008 and it is a proxy of the innovative activity and of the level of human capital. There is common consensus about the importance of the effects of R&D on the aggregate growth of firms and countries, thus we might expect a positive coefficient between the patents variable and economic performance.

$LnTOURISM_i$ is the number of arrivals per inhabitant in the ith province during 2008. Since many regions are specialized in tourism, this variable is included in order to capture the effect of such a sector on the aggregate output (among others who have worked on this we can mention: Balaguer and Cantavella-Jordá, 2002; Proença and Soukiazis, 2008).

All the data come from National Statistical Office of Italy (ISTAT), except for the infrastructure indicator, which comes from Istituto Tagliacarne. Table II presents descriptive statistics of the variables under study. Notably, since all variables are transformed in logarithm term the coefficients can be interpreted as elasticities.

From Figures 1 to 6, it emerges that there are geographical clusters which are related to both criminal activity and per capita income. This may indicate that the legal and illegal activities in a given location depend on the presence of the same activities in the neighbouring areas. If this is the case, then unobserved spatial spillover effects may be present, and a spatial analysis framework may be required.

4. Spatial regression models

When one deals with province or regional data, spill-over effects could be well expected. This means that the observed level of *LnGDP* of a given province could depend not only on its own determinants but also on the *LnGDP* of its neighbours. A high level of income in a particular province could increase the demand for goods in all the surrounding provinces, with a resulting positive impact on their *LnGDP*.

Spatial econometric models are needed which take into account such proximity effects. There are two approaches in the literature to dealing with spatial dependence, the. spatial lag model and the SEM. The SLM can be used to investigate the existence and strength of spatial interaction. In the SLM, not only does Y depend on its characteristics (x_i) but it also depends on the value of its neighbours (x_j). This means that the spatially weighted sum of neighbouring provinces (the spatial lag) is entered as an explanatory variable in the equation as follows:

$$Y = \lambda WY + X\beta + u \quad (2)$$

	Mean	SD	Min	Max
GDP	22,640.56	5,516.027	12,862.22	34,184.65
TOT_CRIME	4,020.565	1,100.784	2,096.111	7,522.109
MURDER	1.028	1.368	0	9.103
ROBBERY	43.552	45.849	3.745	361.718
EXTORTION	10.296	4.759	3.171	27.199
FRAUD	5.051	0.250	4.325	5.805
EMPLOY	45.637	6.938	30.2	57.9
TOURISM	7.390	9.625	0.136	56.081
PATENT	6.851	6.510	0.041	30.386
INFRA	92.674	40.220	23.2	251.8

Notes: number of observations: 103

Table II.
Descriptive statistics

Hence in the SLM the spatially lagged variable WY is included as an additional regressor. Where λ is the spatial dependence parameter typically referred to as the spatial-autoregressive parameter. W is a $n \times n$ standardized spatial weight matrix (where n is the number of observations). X is an $n \times k$ matrix of observations on k right-hand-side exogenous variables. β is the corresponding $k \times 1$ parameter vector. The spatial weight matrix, W, tells us whether any pair of observations are neighbours. The resulting spatial lag WY can be viewed as a spatial weighted average of observations at neighbouring locations and represents the corresponding scalar parameters typically referred to as spatial-autoregressive parameters. ε are *i.i.d.* disturbances. In this case the spatially lagged regressor is correlated with the error term and OLS estimation turns out to be biased and inconsistent due to the simultaneity bias (Anselin, 1988).

In the SEM, spatial dependence is modelled as a spatial autoregressive process in the error term. In matrix notation:

$$Y = X\beta + u; \quad u = \rho Mu + \varepsilon \tag{3}$$

Where Y is an $n \times 1$ vector of observations on the dependent variable, ε are again *i.i.d* disturbances, ρ is the spatial error parameter and M is a $n \times n$ spatial link matrix with zero diagonal elements. Ignoring spatial dependence in the error term does not yield biased least squares estimates. though their variance will be biased, thus resulting in misleading inferences (Anselin, 1988, 1990).

A combined spatial-autoregressive model with spatial-autoregressive disturbances is represented by the SARAR model (Anselin and Florax, 1995). By modelling the outcome for each observation as related to a weighted average of the outcomes of other units, this model determines the outcomes simultaneously (Arraiz *et al.*, 2010; Drukker *et al.*, 2013; Kelejian and Prucha, 2010).

In matrix notation:

$$Y = \lambda WY + X\beta + u; \quad u = \rho Mu + \varepsilon \tag{4}$$

where Y is an $n \times 1$ vector of observations on the dependent variable, X is an $n \times k$ matrix of observations on k right-hand-side exogenous variables. β is the corresponding $k \times 1$ parameter vector. W and M are $n \times n$ spatial link matrix with zero diagonal elements. λ is the spatial dependence parameter and ρ is the spatial error parameter. ε are *i.i.d.* disturbances. The spatial-weighting matrices W and M are known and non-stochastic, and are part of the model definition.

Notably, when $\rho = 0$ and $\lambda \neq 0$, Model (4) reduces to the spatial-autoregressive model (SLM). When $\rho \neq 0$ and $\lambda = 0$ the model becomes the spatial-autoregressive error model (SEM). For $\rho = 0$ and $\lambda = 0$ the model is simply a linear regression model with exogenous variables. Finally, for $\rho \neq 0$ and $\lambda \neq 0$, we have the SLM with a spatial autoregressive disturbance (SARAR). Typically in the SAR and SARE models only one test for one type of dependence is carried out while the other type is considered zero (H_0: $\rho = 0$ and $\lambda = 0$ and vice versa). The SARAR model allows to check the spatial-autoregressive lag and spatial autoregressive disturbance simultaneously and it is employed to carry out the empirical analysis (see Carboni, 2013a, b for a recent application). It useful to highlight that this simultaneity implies that the OLS estimator will not be consistent. Spatial models have many similarities to the moving average model in time series econometrics, in which the error of certain observations may be affected by errors of other observation. In such a case, OLS estimation of SEM will be inefficient because it violates the assumption of independence among disturbance terms. Hence, the classical estimators for standard errors are biased.

According to this approach, the Equation (1) can be rewritten as follows:

$$\begin{aligned} LnGDP_i &= \lambda W * LnGDP_i + \beta_0 + \beta_1 LnCRIME_i + \beta_2 LnEMPLOY_i \\ &\quad + \beta_3 LnINFRA_i + +\beta_4 LnPATENT_i + \beta_5 LnTOURISM_i + u_i \\ &= \rho W * u_i + \varepsilon_i \end{aligned} \tag{5}$$

One crucial feature of spatial analysis is that it takes into account the spatial arrangement of the observational units (locations). This spatial arrangement is represented by a spatial weights matrix W whose non-zero off-elements w_{ij} express the presence or absence (binary weights matrix) or the degree (non-binary weights matrix) of potential spatial interaction between each possible ith and jth pair of locations. Spatial influence enters network autocorrelation models through W (the structure matrix). Entry w_{ij} represents the extent to which y_i is dependent on y_j, and thus to what extent an actor in location j influences an actor in location i. Constructing an a priori constructed spatial weights matrix has the great advantage that spatial interactions across "regions" are collapsed into a single (weighted) variable. However its limitation is that it does not directly test which regions interact with each other nor the strength of such interactions (Harris *et al.*, 2011).

By construction, whatever the type of proximity chosen, the spatial lag WY is an endogenous variable. Hence in autocorrelation models the specification of W is crucially important, since this is designed to estimate ρ and λ (the spatial-autoregressive parameters which measure the extent of these interactions) or β (Leenders, 2002).

Spatial-weighting matrices are employed to compute weighted averages in which more weight is placed on nearby observations than on distant observations (Cliff and Ord, 1981; Haining, 2003) and parameterize Tobler's law of geography "Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). This issue rises concerns on how to measure the distance or contiguity between the observations at different locations. In inverse-distance spatial-weighting matrices, the weights are inversely related to some measure of distance between the locations ($w_{ij} = 1/d_{ij}$ where d_{ij} is the distance between places i and j). These kinds of matrices may allow for all spatial objects to affect each other and are usually normalised to limit dependence. In a row-normalized matrix, the (i, j)th element of becomes e , where Σr_i is the sum of the ith row of . Thus Σr_i denotes the number of actors with whom i has a link. After row normalization, each row will sum to one and every actor receives the same total amount of influence from all actors. Influence of i by j decreases with the number of actors influencing i.

5. Results

5.1 The preliminary analysis

One of the first problems when conducting spatial analysis is detecting potential spatial dependence among observations. If this is not present, there is no need to use special models or methods in the analysis. The most common global test for spatial autocorrelation is based on a statistic developed by Moran (1950). This statistics compares the value of the observed variable at any location with the value of the same variable at neighbouring locations.

Hence Moran's I is used here to analyse the spatial association of the *LnGDP* at province level. This coefficient is fairly simple to compute and interpret. The Moran coefficient is zero in the case of no spatial autocorrelation, irrespective of the analysed variable or spatial system (Hordijk, 1974). If Moran's I is larger than its expected value, then the overall distribution of the observed variables can be seen as characterised by positive spatial autocorrelation. This means that the value of GDP per capita at each location i tends to be similar to the values found for the same variable at spatially contiguous locations.

Table III shows the results of the Moran I test. The value of this statistic is 0.373 while its mean is −0.0098, so there is positive spatial autocorrelation with a highly robust significance (p-value $< 2.2e{-}16$) both with normal approximation and randomized assumptions. This result is confirmed when this statistic is derived from the OLS estimations.

Beside the Moran's I test, the Lagrange multiplier (LM) test and a robust Lagrange multiplier test (robust LM) are performed for both for the SLM and for the SEM. The RLM-error test corrects for the presence of local spatial lag dependence, assuming $\lambda = 0$. The RLM-lag also assumes $\rho = 0$. LM tests are distributed χ^2. The Moran test supplies reliable results for alternative forms of ignored spatial dependence, whereas the LM tests supply indications about the kind of spatial dependence (Anselin and Bera, 1998; Anselin and Florax, 1995). It is worth emphasising that these tests explicitly incorporate the weight distance matrix W, which was discussed above.

In general, the statistic tests indicate that the SLMs perform better than spatial error ones. It is important to highlight that the Moran I test is a global statistic, meaning that it accounts for spatial autocorrelation for all the units but does not supply information about the contribution of each single unit. Local measurements of spatial correlation should be used to compensate for this drawback. Since spatial autocorrelation is detected, the Model (1) is then re-estimated incorporating a correction for spatial error and/or spatial lag, as shown in (5).

5.2 Spatial regression results

There are two steps in the analysis. First, the OLS model is run and tested for spatial autocorrelation. Then, the SLM and the SEM are estimated. In case of significant LM test for residual autocorrelation in SLM approach, we perform a SARAR approach. All the spatial analysis are performed using the maximum likelihood estimation of spatial simultaneous autoregressive error and lag models, implemented in "spdep" package in R (Bivand *et al.*, 2012).

Notably, the results for total crime and fraud give no significant crime coefficients, while we find mixed results for extortion. This may be explained by the fact that total

Moran's I statistics: Lag spatial Tests	Normal approximation	Randomization assumptions
Moran's I	0.373	0.373
Mean	−0.0098	−0.0098
SD	0.0197	0.0197
Z-score	19.490	19.424
p-value[a]	0.0000	0.0000

Note: [a]Two-tailed test

Table III. Tests for spatial autocorrelation crime is a composite index and coarse measure of global crime activity and this is likely to reduce its explanatory power.

Still, murder and robbery show a clear evidence of their negative impact on GDP. Probably the under-reporting problem affects such analysis, as the propensity to report criminal events varies greatly from region to region in Italy. As has been shown by national victimization surveys (ISTAT, 2004), in the South of Italy people report crimes much less often than in the North. For this reason our analysis focuses on the results associated with murder and robbery, in which the problem of under-reporting is limited or negligible.

Table IV report the results for the OLS, SEM, SLM and, if it is the case, SARAR approach. Although the results for the SEM and SLM models do not differ substantially, the SLM has to be preferred since it gives systematically lower AIC (Akaike Information Criterion) values. The null hypothesis of zero spatial error ($\lambda = 0$) can be safely rejected. Parameter λ is positive and strongly significant, indicating spatial-autoregressive dependence. This simply means that the province GDP per capita in a given location is affected by GDP per capita in neighbouring provinces.

Interestingly, the test for residual autocorrelation is significant in three cases: total crime, extortion and fraud. This test indicates the presence of the spatial correlation dependence in the error term also after the inclusion of the spatial lag of the dependent variable. In such cases the SARAR approach is performed giving a no-significant correlation between crime offences and income per capita.

As one can see in Table IV, ρ is significant in all the cases analysed. Typically this form of dependence is not connected to the spatial structure, but only indicates measurement errors (e.g. the administrative boundaries for collecting information do not accurately reflect the nature of the underlying process which generates the sample data). These parameters do not, indeed, have a direct economic interpretation.

Going to murder (Model 2) and robbery (Model 3) specifications, the results in Table IV indicate that crime has a detrimental effect on GDP: an 1 per cent increase in the homicide and robbery rate reduces income per capita by 0.038 and 0.033 per cent, respectively.

Interestingly, this negative impact is a direct spatial effect. As is the case in a time series framework, a type of long-run-estimation can be estimated which takes into account both direct and indirect effects. Thus the coefficients in Table IV measure the instantaneous effect on the GDP of the ith province caused by shocks in the GDP of the neighbouring provinces. According to our definition (Equation (6)), such a change in the GDP of the ith province causes a variation in the economic performance of its neighbour, and as a result this affects the ith province. The total spatial effect can be calculated by multiplying the coefficients of Table IV with the spatial multiplier matrix $[I–\lambda W]^{-1}$ and dividing by the number of regions, as follows:

$$K = \frac{[I - \lambda W]^{-1}}{N} \tag{6}$$

The trace of this matrix K represents the spatial multiplier (LeSage and Pace, 2009). The global effects of the explanatory variables on the income per capita can be calculated by multiplying this parameter with each coefficient.

In the case of the Equation (2) in Table IV, K values of about 1.075 indicating that the total spatial effects are 1.075 times the direct coefficients. The value of the

	TOT_CRIME (1)				MURDER (2)			ROBBERY (3)		
Variables	OLS	SEM	SLM	SARAR	OLS	SEM	SLM	OLS	SEM	SLM
LnCRIME	0.043	−0.0009	0.019	0.034	−0.045**	−0.045***	−0.037***	−0.061***	−0.051***	−0.033**
LnEMPLOY	−0.081	0.005	−0.025	−0.051	−0.046	0.025	0.001	−0.05	0.007	−0.014
LnINFRA	−0.004	0.044	0.021	−0.006	0.012	0.042*	0.029	0.087**	0.107***	0.068**
LnPATENT	0.195***	0.065***	0.079***	0.075***	0.186***	0.058***	0.072***	0.187***	0.069***	0.079***
LnTOURISM	0.028**	0.011	0.012	0.009	0.028**	0.008	0.011	0.024**	0.010	0.010
Constant	11.893***	10.423***	4.271***	3.810***	11.950***	10.282***	4.267***	11.887***	10.344***	4.511***
ρ		0.884***		−0.842***		0.889***			0.8820***	
λ			0.635***	0.687***			0.630***			0.613***
AIC	−123.10	−163.65	−181.09	−187.01	−128.20	−174.18	−188.38	−130.41	−172.18	−184.92
Test (a)		−0.111	0.011	0.043		0.031	−0.087		−0.059	−0.010
F-test (b)		10.84***	11.825***	11.825***		5.927**	5.718**		3.707*	3.880*
Test (c)			5.261**				1.995			1.228
LMerr	4.918**				7.799***			11.025***		
RLMerr	2.350				0.660			0.040		
LMlag	53.166				54.313***			51.881***		
RLMlag	50.598				47.175***			40.896***		
	EXTORTION (4)				FRAUD (5)					
Variables	OLS	SEM	SLM	SARAR	OLS	SEM	SLM	SARAR		
LnCRIME	−0.124***	−0.064**	−0.048*	−0.020	0.019	−0.016	−0.015	−0.018		
LnEMPLOY	−0.053	0.004	−0.017	−0.033	−0.081	0.008	−0.019	−0.033		
LnINFRA	0.063*	0.069**	0.047*	0.017	0.007	0.048*	0.033	0.012		
LnPATENT	0.165***	0.061***	0.074***	0.074***	0.197***	0.064***	0.079***	0.074***		
LnTOURISM	0.028***	0.013	0.013*	0.010	0.029**	0.011	0.012	0.010		
Constant	11.819***	10.408***	4.716***	4.144***	12.119***	10.461***	4.386***	3.934***		
ρ		0.873***		−0.709***		0.884***		−0.808***		
λ			0.597***	0.668***			0.639***	0.695***		
AIC	−135.56	−167.97	−184.15	186.85	−122.77	−163.79	181.07	−186.48		
Test (a)		−0.001	0.025	0.011		0.170	0.056	0.028		
F-test (b)		29.254***	14.277***	14.277***		19.877***	18.651***	18.651***		
Test (c)			2.800*				5.135**			
LMerr	6.017**				5.261**					
RLMerr	0.871				2.116					
LMlag	45.744***				53.124***					
RLMlag	40.598***				49.980***					

Notes: Instrumented: CRIME; Instruments: spatial lagged CRIME. AIC is the Akaike's Information Criterion; Test (a): Hausman test; Test (b): First-stage *F*-statistics on excluded instruments; Test (c): Test for residual autocorrelation; LMerr, RLMerr, LMlag and RLMlag stand for Lagrange Multiplier tests for spatial error (LMerr) and for spatial lag dependence (LMlag) and Robust Lagrange Multiplier tests for spatial error (RLMerr) and for spatial lag dependence (RLMlag), respectively. *,**,***Significance at the 10, 5 and 1 per cent, respectively

Table IV.
Regression results

spatial multiplier implies that direct effects are more relevant than indirect ones. To be more precise, the indirect effects are 7.5 per cent of direct spatial effects. Indeed the global impact of a one per cent increase in murders is about −0.040 per cent in GDP. Thus, if the number of murders will double, GDP per capita is reduced by about 900 euros.

Looking at Equation (3) in Table IV, K is about 1.069. Still, multiplying such value times the coefficient associated with robbery rate we find a value equals to −0.035. So, a one per cent increase in robbery leads to a decrease in GDP per capita by 0.035 per cent, including direct and indirect effects. This implies that if the number of robberies doubles, GDP per capita is reduced by some 800 euros.

We recall that such estimates represent crime-GDP elasticities, i.e. the marginal costs associated to one per cent increase in murder and robbery activity. As highlighted by Soares (2015), the marginal cost analysis is a more powerful tool in calibrating optimal policy than the social cost of crime-related to the total loss caused by crime.

5.3 Robustness check

An important limitation of such an analysis is the possible bidirectional causality between crime and economic output. As mentioned in Section 1, crime may well be not exogenous, since one might expect that economic fluctuations would impact criminal activities. Unfortunately, such endogeneity may affect our findings, leading to possibly biased estimates.

At this point we need to identify a variable correlated with homicide rates but not with income. Drawing inspiration from Anselin (1988, pp. 208-209) and Zietz *et al.* (2008), a natural choice of the instrument may be the vector which consists of linearly independent columns of $WCRIME = W \times CRIME$. This represents the spatial weight average of homicides in the neighbourhood of a given province, and thus provides an instrument for measuring its crime level. The hypothesis is that an economic shock in the ith province probably affects its crime level but it does not impact the average level of crime in its neighbourhood as a whole. In this sense, economic fluctuations in a given province have a negligible effect on the weighted average of crime in the closest nearby provinces. We are implicitly assuming that the spatially lagged crime variable may affect local GDP through both local crimes and other unobservable factors (which we check for with the spatial econometric model).

The robustness of our instruments has been checked by including them as a regressor in the baseline model (Pan *et al.*, 2012). The results reveal that the coefficients are not statistically significant. The validity of the instruments is further corroborated by the first-stage F-statistics on excluded instruments (reported in Table IV). As shown in Table IV, the Hausman test is performed for each specification. The results indicate that the null hypothesis of exogeneity of crime with respect to GDP cannot be rejected.

6. Conclusions

Crime is an important social phenomenon that directly and indirectly affects all economic agents. Recently, Detotto and Vannini (2010) found that in Italy the social costs of criminal activities were about €38 billion, or about 2.6 per cent of Italian GDP. This result is particularly impressive when one considers that the authors could only gauge the costs associated with a subset of offences which amounted to only 64 per cent of total recorded crimes in 2006.

Following the recent literature on crime and growth, this paper proposes a cross-section analysis based on a sample of 103 Italian provinces, in order to investigate the potential relationship between these two variables, and to check for possible spatial effects. The analysis confirms the presence of spatial correlation among the provinces by using the inverse-distance spatial-weighting matrices, in which the weights are inversely related to Euclidean distance between the locations.

A linear cross-sectional spatial-autoregressive model and a spatial-autoregressive disturbances model is employed. In line with the recent literature on economic growth, the findings show that crime has a detrimental effect on added value. To be more precise, an increase by 1 per cent in the homicide and robbery rate reduces economic output by 0.038 and 0.033 per cent, respectively. When the total effects are considered, the impact of crime is −0.040 and −0.035 per cent, respectively. Interestingly, total crime, extortion, and fraud do not show clear evidence of their negative effects on economic output.

These results may be due to the under-reporting of such crimes. Official data only represents the observable component of crime, and this depends on both the efficiency/efficacy of the police and on the residents' propensity to report crimes. Unfortunately such propensity to report crime is not constant all over the country, and is higher in the North than in the South (ISTAT, 2004). This can lead to biased estimates of crime coefficients. Since robbery and murder are the most reliable of all crime variables, and consequently less affected by underreporting problems, we are able to estimate their negative impact on GDP.

References

Anselin, L. (1988), *Spatial Econometrics: Methods and Models*, Kluwer Academic Publishers, Boston, MA.

Anselin, L. (1990), "Some robust approaches to testing and estimation in spatial econometrics", *Regional Science and Urban Economics*, Vol. 20 No. 2, pp. 141-163.

Anselin, L. and Bera, A.K. (1998), "Spatial dependence in linear regression models with an introduction to spatial econometrics", in Ullah, A. and Davide, E.A.G. (Eds), *Handbook of Applied Economic Statistics*, Marcel Dekker, New York, NY, pp. 237-290.

Anselin, L. and Florax, R.J.G.M. (1995), "Small sample properties of tests for spatial dependence in regression models: some further results", in Anselin, L. and Florax, R.J.G.M. (Eds), *New Directions in Spatial Econometrics*, Springer, New York, NY, pp. 21-74.

Arraiz, I., Drukker, D.M., Kelejian, H.H. and Prucha, I.R. (2010), "A spatial cliff-ord-type model with heteroskedastic innovations: small and large sample results", *Journal of Regional Science*, Vol. 50 No. 2, pp. 592-614.

Ashby, J.N. and Ramos, M.A. (2013), "Foreign direct investment and industry response to organized crime: the Mexican case", *European Journal of Political Economy*, Vol. 30 No. C, pp. 80-91.

Aschauer, D.A. (1989), "Is public expenditure productive?", *Journal of Monetary Economics*, Vol. 23 No. 2, pp. 177-200.

Balaguer, J. and Cantavella-Jordá, M. (2002), "Tourism as a long-run economic growth factor: the Spanish case", *Applied Economics*, Vol. 34 No. 7, pp. 877-884.

Barro, R.J. (1991), "Economic growth in a cross section of countries", *The Quarterly Journal of Economics*, Vol. 106 No. 2, pp. 407-443.

Bivand, R., Altman, M., Anselin, L., Assunção, R., Berke, O., Bernat, A., Blanchet, G., Blankmeyer, E., Carvalho, M., Christensen, B., Chun, Y., Dormann, C., Dray, S., Halbersma, R., Krainski, E., Legendre, P., Lewin-Koh, N., Li, H., Ma, J., Millo, G., Mueller, W., Ono, H., Peres-Neto, P., Piras, G., Reder, M., Tiefelsdorf, M. and Yu, D. (2012), "spdep: spatial dependence: weighting schemes, statistics and models", r package version 0.5-46 available at: http://CRAN.R-project.org/package=spdep (accessed 19 September 2014).

Canning, D. (1999), "Infrastructure's contribution to aggregate output", Working Paper No. 2246, The World Bank Policy Research, Washington, DC, November.

Cantor, D. and Land, K.C. (1985), "Unemployment and crime rates in the post-world war II United States: a theoretical and empirical analysis", *American Sociological Review*, Vol. 50 No. 3, pp. 317-332.

Carboni, A.O. (2013a), "A spatial analysis of R&D: the role of industry proximity", *Economics of Innovation and New Technology*, Vol. 22 No. 8, pp. 820-839.

Carboni, A.O. (2013b), "Spatial and industry proximity in collaborative research: evidence from Italian manufacturing firms", *The Journal of Technology Transfer*, Vol. 38 No. 6, pp. 896-910.

Cliff, A.D. and Ord, J.K. (1981), *Spatial Processes: Models and Applications*, Pion Ltd, London.

Cohen, A.M. (2000), "Measuring the costs and benefits of crime and justice", *Criminal Justice*, Vol. 4, pp. 263-315.

Daniele, V. and Marani, U. (2011), "Organized crime, the quality of local institutions and FDI in Italy: a panel data analysis", *European Journal of Political Economy*, Vol. 27 No. 1, pp. 132-142.

Davidson, R. and MacKinnon, J.G. (1989), "Testing for consistency using artificial regressions", *Econometric Theory*, Vol. 5 No. 3, pp. 363-384.

Davidson, R. and MacKinnon, J.G. (1993), *Estimation and Inference in Econometrics*, University Press, Oxford.

Del Monte, A. and Papagni, E. (2001), "Public expenditure, corruption, and economic growth: the case of Italy", *European Journal of Political Economy*, Vol. 17 No. 1, pp. 1-16.

Demetriades, P. and Mamuneas, T. P. (2000), "Intertemporal output and employment effects of public infrastructure capital: evidence from 12 OECD economies", *The Economic Journal*, Vol. 110 No. 465, pp. 687-712.

Detotto, C. and Otranto, E. (2010), "Does crime affect economic growth?", *Kyklos*, Vol. 63 No. 3, pp. 330-345.

Detotto, C. and Otranto, E. (2012), "Cycles in crime and economy: leading, lagging and coincident behaviors", *Journal of Quantitative Criminology*, Vol. 28 No. 2, pp. 295-317.

Detotto, C. and Pulina, M. (2013), "Does more crime mean fewer jobs and less economic growth?", *European Journal of Law and Economics*, Vol. 36 No. 1, pp. 183-207.

Detotto, C. and Vannini, M. (2010), "Counting the cost of crime in Italy", *Global Crime*, Vol. 11 No. 4, pp. 421-435.

Drukker, D.M., Egger, P. and Prucha, I.R. (2013), "On two-step estimation of a spatial autoregressive model with autoregressive disturbances and endogenous regressors", *Econometric Reviews*, Vol. 32 Nos 5-6, pp. 686-733.

Field, S. (1990), "Trends in crime and their interpretation: a study of recorded crime in post-war England and Wales", *Home Office Research Study,* Vol. 119, Home Office, London, 95pp.

Forni, M. and Paba, S. (2000), "The sources of local growth: evidence from Italy", *Giornale degli Economisti e Annali di Economia*, Vol. 59 No. 1, pp. 1-49.

Freckleton, M., Wright, A. and Craigwell, R. (2012), "Economic growth, foreign direct investment and corruption in developed and developing countries", *Journal of Economic Studies*, Vol. 39 No. 6, pp. 639-652.

Gaibulloev, K. and Sandler, T.M. (2008), "Growth consequences of terrorism in western Europe", *Kyklos*, Vol. 61 No. 3, pp. 411-424.

Goulas, E. and Zervoyianni, A. (2013), "Economic growth and crime: does uncertainty matter?", *Applied Economics Letters*, Vol. 20 No. 5, pp. 420-427.

Haining, R. (2003), *Spatial Data Analysis: Theory and Practice*, Cambridge University Press, Cambridge.

Harris, R., Moffat, J. and Kravtsova, V. (2011), "In search of 'W' ", *Spatial Economic Analysis*, Vol. 6 No. 3, pp. 249-270.

Hillman, A.L. and Schnytzer, A. (1986), "Illegal economic activities and purges in a soviet-type economy: a rent-seeking perspective", *International Review of Law and Economics*, Vol. 6 No. 1, pp. 87-99.

Hordijk, L. (1974), "Spatial correlation in the disturbances of a linear interregional model", *Regional and Urban Economics*, Vol. 4 No. 2, pp. 117-140.

ISTAT (2004), La sicurezza dei cittadini. reati, vittime, percezione della sicurezza e sistemi di protezione, ISTAT, Roma.

Kelejian, H.H. and Prucha, I.R. (2010), "Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances", *Journal of Econometrics*, Vol. 157 No. 1, pp. 53-67.

Leenders, R.T.A.J. (2002), "Modelling social influence through network autocorrelation: constructing the weight matrix", *Social Networks*, Vol. 24 No. 1, pp. 21-47.

LeSage, J. and Pace, R.K. (2009), *Introduction to Spatial Econometrics*, Chapman and Hall/CRC, Boca Raton, FL.

Mauro, P. (1995), "Corruption and growth", *The Quarterly Journal of Economics*, Vol. 110 No. 3, pp. 681-712.

Mauro, L. and Carmeci, G. (2007), "A poverty trap of crime and unemployment", *Review of Development Economics*, Vol. 11 No. 3, pp. 450-462.

Mehlum, H., Moene, K.O. and Torvik, R. (2005), "Crime induced poverty traps", *Journal of Development Economics*, Vol. 77 No. 2, pp. 325-340.

Mehlum, H., Moene, K.O. and Torvik, R. (2006), "Institutions and the resource curse", *The Economic Journal*, Vol. 116 No. 508, pp. 1-20.

Mendez, F. and Sepulveda, F. (2006), "Corruption, growth and political regimes: cross country evidence", *European Journal of Political Economy*, Vol. 22 No. 1, pp. 82-98.

Moran, P.A.P. (1950), "Notes on continuous stochastic phenomena", *Biometrika*, Vol. 37 Nos 1-2, pp. 17-23.

Pan, M., Widner, B. and Enomoto, C.E. (2012), "Growth and crime in contiguous states of Mexico", *Review of Urban & Regional Development Studies*, Vol. 24 Nos 1-2, pp. 51-64.

Pellegrini, L. and Gerlagh, R. (2004), "Corruption's effect on growth and its transmission channels", *Kyklos*, Vol. 57 No. 3, pp. 429-456.

Peri, G. (2004), "Socio-cultural variables and economic success: evidence from Italian provinces 1951-1991", *Topics in Macroeconomics*, Vol. 4 No. 1, pp. 1-34.

Proença, S. and Soukiazis, E. (2008), "Tourism as an economic growth factor: a case study for Southern European countries", *Tourism Economics*, Vol. 14 No. 4, pp. 791-806.

Soares, R.R. (2015), "Welfare costs of crime and common violence", *Journal of Economic Studies*, Vol. 42 No. 1, pp. 117-137.

Tobler, W. (1970), "A computer movie simulating urban growth in the Detroit region", *Economic Geography*, Vol. 46 No. 2, pp. 234-240.

Tullock, G. (1967), "The welfare costs of tariffs, monopolies, and theft", *Western Economic Journal*, Vol. 5 No. 3, pp. 224-232.

Zietz, J., Zietz, E. and Sirmans, S. (2008), "Determinants of house prices: a quantile regression approach", *Journal of Real Estate Finance and Economics*, Vol. 37 No. 3, pp. 317-333.

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