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THE ECONOMIC CONSEQUENCES OF CRIME IN ITALY

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WORKING PAPERS

2013/03

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Title: THE ECONOMIC CONSEQUENCES OF CRIME IN ITALY

ISBN: 978 88 8467 810 2

First Edition: February 2013

Via Is Mirrionis, 1
09123 Cagliari
Tel./Fax 070 291201
www.cuec.it

The economic consequences of crime in Italy

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Abstract

This paper employs provincial data to study the relationship between several crime typologies, namely murder, theft, robbery and fraud, and economic output in Italy. We employ 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. The model used here combines a spatial autoregressive model with autoregressive disturbances. In modelling the outcome for each location depends on a weighted average of the outcomes of other locations. Outcomes are determined simultaneously. The results of the spatial two stage least square estimation suggest that the homicide rate has a negative impact on Italian gross domestic product while theft, robbery and fraud do not affect economic output and that there are beneficial spill-overs from neighbouring provinces.

Keywords: spatial weights; spatial models; growth; crime; crowding-out effect.

JEL Classifications: C31, K10, O18, R11

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 at macro level has become an important field of study in recent decades. According to Field (1990), two opposite causal effects can be observed.

On the one hand, economic fluctuations has 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, 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. Indeed crime has huge economic costs for society, as has been demonstrated in several empirical studies. 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. Peri (2004) measured the impact of murders on the annual per capita income growth in Italy, checking for a set of explanatory variables. Pellegrini and Gerlagh (2004) found that corruption affects economic growth by reducing the ratio of investment to gross domestic product (GDP), as well as the country's openness. 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. Detotto and Otranto (2010) applied a time variable 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. 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. More recently Goulas and Zervoyianni (2013) used a panel of 25 countries over the period 1991 to 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.

This analysis contributes to the above mentioned empirical literature by studying the impact of crime on GDP in a sample of 103 Italian provinces. Illicit Italian activity consists mainly of property crimes, i.e. thefts, robberies and fraud, in all of which the economic motivations of the criminals play a significant role (Detotto and Pulina, 2013). Hence from this perspective, Italy is an interesting case for crime related studies because crime may play an important role in explaining economic performance. In this framework, several crime indicators are used: total crime, theft, robbery, fraud and murder. Total crime measure the aggregate level of criminal activity in a region, while theft, robbery and fraud are typical property crimes that reallocate resources from legal to illegal activities and reduce consumption and investment. However since such crimes are seriously under reported, here we propose using the murder rate as the total crime index. We use a spatial econometric approach, in order to take into account possible spill-over effects among the provinces. 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 model used here combines the spatial autoregressive model with autoregressive disturbances (SARAR). Hence unlike traditional spatial analysis, which typically considers only one spatial dependence at a time (either lag or error component) while the other type of dependence is set as equal to zero, in this work the spatial autoregressive lag dependence and spatial autoregressive error dependence are modelled simultaneously (Anselin and Florax, 1995).

The results of the spatial two stage least square estimation suggest that crime negatively impacts GDP. To be more precise, total crime and property crimes do not seem to affect economic output, while the effects of murders are statistically significant. In other words, an increase in the murder rate reduces economic output by 0.048. Our findings also indicate that there are positive spill-over effects among the provinces. We find that an increase in the average level of GDP among neighbouring provinces leads to an increase of 0.69 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 (IV) approach is proposed. This uses the spatial lagged murder rates as an instrument to describe the level of homicides in a given province.

The article is organized as follows. Section 2 provides a description of the data set and the variables used. Section 3 describes the theory underlying the spatial regression models. Section 4 presents results and comments. Section 5 concludes.

2. Description of the data

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

$$GDP_i = \beta_0 + \beta_1 CRIME_i + \beta_2 INFRA_i + \beta_3 PATENT_i + \beta_4 TOURISM_i + \beta_5 NORTH_i + \varepsilon_i \qquad (1)$$

where GDP_t is the income per capita in the *i*-th province in 2010 and ε_i is the error term.

CRIME measures the number of offences per 100,000 inhabitants in 2008. Five crime typologies are tested: total crime, theft, robbery, fraud and murder. 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 decided that the number of homicides can be considered as a proxy for criminal activity. The homicide rates are the most reliable of all crime variables and, especially in hot spots of Mafia or other similar criminal activity, they may provide a rough indicator of organized crime. The co-relationship coefficients between homicide rates and other crime types also seem to be statistically different from zero, as shown in Table 1.

$INFRA_i$ indicates the level of infrastructure in a given province in 2001. As shown by Aschauer (1989), the stock of public infrastructure capital is a significant determinant of aggregate total factor productivity (TFP). Canning (1999) and Demetriades and Mamuneas (2000) find a significant positive relationship between output and infrastructure in a cross-country panel data context.

$PATENT_i$ measures the number of patents per inhabitant in 2009 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.

$TOURISM_i$ is the number of arrivals in the *i*-th province during 2010. Since many regions are specialize 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).

NORTH is a dummy variable that has a value of one if the province is in North Italy and zero otherwise. It is designed to take into account the structural differences in the economy in North and South Italy. All the data come from National Statistical Office of Italy (ISTAT), except for the infrastructure indicator, which comes from Istituto Tagliacarne. All variables are transformed into logarithmic terms. Table 2 presents descriptive statistics of the studied variables.

3. Spatial Regression Models

Spillover effects could be expected from province data from different provinces. This means that the observed level of GDP of a given province could depend not only on its own determinants but also on the GDP 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 GDP.

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 spatial error model. The spatial lag model (SAR) can be used to investigate the existence and strength of spatial interaction. In the spatial lag model, 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:

$$\mathbf{Y} = \lambda\mathbf{WY} + \mathbf{X\beta} + \mathbf{u} \tag{2}$$

Hence in the spatial lag model 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 spatial error model (SARE), spatial dependence is modelled as a spatial autoregressive process in the error term. In matrix notation:

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

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., 2010; Kelejian and Prucha, 2010):

In matrix notation:

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

where Y is an $n\times1$ 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 $k\times1$ 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 (SAR). When $\rho \neq 0$ and $\lambda = 0$ the model becomes the spatial-autoregressive error model (SARE). For $\lambda = 0$ and $\rho = 0$ the model is simply a linear regression (LR) model with exogenous variables. Finally, for $\rho \neq 0$ and $\lambda \neq 0$, we have the spatial lag model 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, 2012, 2013 for a recent application). It useful to highlight that this simultaneity implies that the ordinary least squares (OLS) estimator will not be consistent. Spatial models have many similarities to the moving average (MA) 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 spatial error model will be inefficient because it violates the assumption of independence among disturbance term. Hence, the classical estimators for standard errors are biased.

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

$$\begin{gathered} GDP_i = \lambda W^*GDP_i + \beta_0 + \beta_1 INFRA_i + \beta_2 PATENT_i + \beta_3 TOURISM_i + \beta_4 CRIME_i + \beta_5 NORTH_i + u_i \\ u_i = \rho W^* u_i + \varepsilon_i \end{gathered} \tag{5}$$

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 i-th and j-th 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 normalized to limit dependence. In a row-normalized matrix, the *(i, j)*-th element of $\tilde{W}$ becomes e $\tilde{w} = w_{ij} / \Sigma r_i$, where Σr_i is the sum of the i–th row of $\tilde{W}$. 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.

4. Empirical results

The preliminary analysis

One of the main assumptions in ordinary least squares regression is the homogeneity of variance of the residuals. Before proceeding further, the Breusch–Pagan test is employed on the residuals of the original linear model (1) for different types of crime. In all the OLS regressions in which each crime type (total crime, theft, robbery, fraud or murder) is used, the chi-square have critical values of less than 90% [1], which indicates that heteroscedasticity is not likely to be a problem for the sample we used. It is worth recalling that the OLS model does not take into account spatial spill-overs among the units.

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 GDP per 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 characterized 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 3 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*=0.0000) 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 spatial lag model and for the spatial error model. 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

[1] Results of the statistical tests are available upon request.

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 results for spatial error show no evidence of spatial error dependence either in the LM-error or the RLM-error, while the LM-lag and the RLM-lag statistics suggest that spatial lag dependence is likely to be an issue[2]. 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, and given the absence of heteroscedasticity, the model (1) is then re-estimated incorporating a correction for both spatial error and spatial lag, as shown in (5). An important limitation of such an analysis is the possible bidirectional causality between crime and economic output. As mentioned in section 1, crime is not exogenous, since one might expect that economic fluctuations would impact criminal activities. Unfortunately, such endogeneity affects our findings, leading to 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), we use a $W \times CRIME$ vector. 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 i-th 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.

The *spivreg* (spatial two stage least square estimation with additional endogenous variables) routine is used to do this. It is available in STATA and was developed by Drukker et al (2011). The *spivreg* command implements the GMM/IV estimation strategy discussed for the SARAR models in Arraiz et al. (2010) and Drukker et al. (2010).

[2] Lagrange multiplier (LM) and robust Lagrange multiplier tests are available upon request.

Hence, the model is a linear cross-sectional spatial-autoregressive model with additional endogenous variables, exogenous variables, and spatial-autoregressive disturbances.

$$\begin{aligned} \mathbf{y} &= \pi\mathbf{Y} + \lambda\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{u} \\ \mathbf{u} &= \rho\mathbf{M}\mathbf{u} + \varepsilon \end{aligned} \tag{6}$$

Where, unlike the spatial models discussed above, the term Y is included among the regressors. This latter is an $n \times p$ matrix of observations on p RHS endogenous variables, and π is the corresponding $p \times 1$ parameter vector. This is a spatial-autoregressive model with spatial autoregressive disturbances (SARAR), exogenous regressors, and additional endogenous regressors. Spatial interactions are modelled through spatial lags, and the model allows for spatial interactions in the dependent variable, the exogenous variables, and the disturbances. In this case $W=M$ (i.e. spatial lag and spatial error are modelled on the same weight matrix).

Regression results

There are two steps in the analysis. Firstly, the OLS model is run and tested for heteroscedasticity and spatial autocorrelation. Then, the combined spatial-autoregressive model with spatial-autoregressive disturbances is estimated using an instrumental variable approach. Unfortunately the results for total crime, theft, robbery and fraud give no significant crime coefficients, although their sign, as expected, was negative. 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, which is taken as the crime index. For murders the problem of under-reporting is negligible, and they are significantly correlated with total crimes and property crimes, as shown in Table 1.

Since the tests for the absence of spatial autocorrelation can be rejected (see Table 3), we can pass to the further step in which Equation (1) and (6) can be regressed. The two columns of Table 4 report the results for the OLS and the IV approach, correcting for spatial dependence for this sample of 103 Italian provinces. Although the results for the two models do not differ substantially, the spatial two stage least square estimation shows clear evidence of spatial spill-overs. The null hypothesis of zero spatial error (λ=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 parameter ρ is not significant, which indicates the absence of spatial-autoregressive dependence in the error term. In other words, the inclusion of the spatial lag of the dependent variable completely eliminates the spatial correlation from the disturbances.

Column (3) of Table 4 represents the spatial IV regression including only the spatial lag term, indicating that the results seem to be quite robust. The results in Table 4 indicate that all the variables included in model (5) positively affect the income per capita, with the exception of the crime variable. To be more precise, crime has a detrimental effect on GDP: an increase in the homicide rate reduces income per capita by 0.048. The level of infrastructure also has a significant effect on GDP, i.e. an increase in this indicator leads to a rise of 0.069 in added value per capita. As expected, tourism has a positive impact on the aggregate economic output but such an effect is not significant at the 90% level. The number of patents per capita is here taken a measure at province level of innovative activity and of the level of human capital. Its effect is about 0.039. Finally, as expected, the NORTH dummy captures the economic structural differences between the North and South of Italy: on average, in Northern provinces income per capita levels are about 0.13 higher.

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 4 measure the instantaneous effect on the GDP of the *i*-th 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 *i*-th province causes a variation in the economic performance of its neighbour, and as a result this affects the *i*-th province. The total spatial effect can be calculated by multiplying the coefficients of Table 4 with the spatial multiplier matrix $[I - \lambda W]^{-1}$ and dividing by the number of regions, as follows:

$$K = \frac{[I - \lambda W]^{-1}}{N} \tag{7}$$

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

K values of about 1.026 indicate that the total spatial effects are 1.026 times the direct coefficients of Table 4. The value of the spatial multiplier implies that direct effects are more relevant than indirect ones. To be more precise, the indirect effects are 2.6% of direct spatial effects. Indeed the general crime impact is about -0.049. Finally, the total spatial effects of infrastructure stock and patenting activity are 0.040 and 0.071, respectively.

5. 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% 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% 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 with additional endogenous variables, exogenous variables, and spatial-autoregressive disturbances is employed. The IV approach is needed because there may be a bidirectional causal relationship between crime and economic outcome. For this reason the spatial weighted average of homicides is used as instrument for defining the overall crime levels.

As expected, empirical analysis indicates that tourism infrastructure stock and patenting activity all have positive effects. Positive spatial spill-overs are also found among Italian provinces. In other words, income per capita in a given province benefits from the economic performance of its neighbouring provinces.

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 in the homicide rate reduces economic output by 0.048. When the total effects are considered, the impact of crime is -0.049. Interestingly, total crime and property crimes, namely theft, robbery and fraud, do not have any 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. This can lead to biased estimates of crime coefficients. In order to overcome such problems we used homicide rates as the crime activity indicator, because they are the most reliable of all crime variables and they have a statistically significant co-relationship with total crime and property crimes. In addition it is well known that a percentage of the murders are caused by Mafia activity, especially in the South, and this allows murder rates to be used as a rough indicator of organized crime activity.

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Table 1 - Correlation coefficients among crime typologies in logarithm terms: one-tailed Pearson test (number of observations: 103)

	TOTAL CRIME	MURDER	THEFT	ROBBERY	FRAUD
TOTAL CRIME	1.0000				
MURDER	0.1866**	1.0000			
THEFT	0.9196***	0.1222^	1.0000		
ROBBERY	0.6861***	0.3628***	0.6928***	1.0000	
FRAUD	0.5012***	0.1859**	0.3051***	0.4387***	1.0000

^, *, ** and *** indicate significance at the 15%, 10%, 5% and 1%, respectively.

Table 2 - Descriptive statistics (number of observations: 103)

	Mean	s.d.	Min	Max
GDP	250512.8	61675.69	140883	460921
CRIME	3990.3	1086.0	2096.5	7399.0
MURDER	1.0	1.3	0	9.1
THEFT	1897.3	755.7	663.6	4297.0
ROBBERY	43.3	45.8	3.7	362.7
FRAUD	160.1	41.7	75.9	332.9
INFRASTRUCTURE	94.2	39.7	29	238
TOURISM	7.2	9.3	0.4	56.5
PATENT	3.3	3.6	0.1	23.1
NORTH	0.6	0.5	0	1

Table 3 - Tests for Spatial Autocorrelation

Moran's I Statistics: Lag spatial

Tests	Statistic	P-Value
	Normal Approximation	Randomization Assumptions
Moran's I	0.373	0.373
Mean	-0.0098	-0.0098
Std dev	0.0197	0.0197
Z-score	19.490	19.424
P-value*	0.0000	0.0000

* Two-tailed test

Table 4 - Regression results

Dependent variable: VALUE ADDED	OLS		Spatial autoregressive IV-model (GS2SLS)§		Spatial autoregressive IV-model (GS2SLS)§	
	Coef.	SE	Coef.	SE	Coef.	SE
MURDER	-0.038***	0.013	-0.044**	0.018	-0.048**	0.020
INFRASTR.	0.066*	0.035	0.069**	0.032	0.069**	0.033
TOURISM	0.023*	0.012	0.023**	0.010	0.019	0.011
PATENT	0.049***	0.014	0.038***	0.013	0.039***	0.014
NORTH	0.280***	0.041	0.13***	0.05	0.15***	0.05
Constant	11.858***	0.154	2.04	2.48	3.35	2.78
Lambda			0.79***	0.20	0.69***	0.23
Rho			-0.84	0.80	-	-

§Instrumented: *CRIME*; Instruments: spatial lagged *CRIME*
*, ** and *** indicate significance at the 10%, 5% and 1%, respectively.

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Finito di stampare nel mese di Marzo 2013
Presso **Copy…Right! studio grafico & stampa digitale**
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ISBN 978-88-84-67-810-2