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# Crime versus Organized Crime in Italy: Do their Drivers Differ?

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# Crime versus Organized Crime in Italy: Do their Drivers Differ?

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**Abstract**

This paper empirically examines the determinants of organized crime and of common crime in a panel of Italian regions over the period 1983-2003. In line with the literature, these factors include economic, socio-demographic, and crime-deterrence indicators. The analysis shows that both organized and common crimes respond symmetrically to some drivers, such as crime-deterrence variables and the share of a region's economically active population, reducing both categories of crime. At the same time, there are drivers that influence only one of these types of crime, with higher education and population density both raising organized crime. Overall, this study points to the importance of disentangling the examination of the factors that drive organized crime from those of common crime, useful for the development of strategies specific to addressing each type of crime.

*Keywords*: Crime; organized crime; determinants; Italy

*JEL Classification*: C23; K42

## 1. Introduction

Criminal behavior has been the subject of considerable research over the past three decades. This research has led to the broad consensus that criminal activities pose a serious threat to both economies and societies. This, in turn, has led to the examination of the determinants of crime as a way of improving our understanding of its development and in forming policies appropriate for its confinement. Most of the literature has investigated the drivers of individual or common crime, with only recent efforts directed in unveiling the factors that shape organized crime (OC). Given the differences in the underlying structure, organization and formation of the two types of crime, however, it is critical to assess whether both types of crime are influenced by the same factors, and if so, by which ones. To this extent, this paper contributes to the literature by providing an empirical analysis that jointly studies (and compares) the drivers of both individual crime and organized crime. We do this with reference to Italy due to the long presence of criminal organizations that allow the generation of credible measures of OC activity.

There exists a long literature investigating the determinants of individual crime. Becker (1968)'s pioneering work on the economics of crime first illustrated that even individuals who are involved in illegal activities behave rationally. According to the standard economic model of crime (EMC), an individual rationally decides whether or not to commit crime and how much crime to commit, by comparing the benefits and costs of legal and illegal activities taking into account the probability of being arrested and punished. Following this approach, most of the subsequent economic analysis of crime has focused on the individual agents' optimal choice between legal and illegal activities (e.g., Ehrlich, 1973; Taylor, 1978; Levitt, 1996).[1] In this environment, a rich empirical literature has identified that the frequency of criminal offenses is influenced by factors, such as the probability of apprehension and punishment, differential wages between legal and illegal activities, level of education, unemployment, cultural and family background, and other economic and socio-demographic factors that include gender, age and population density (e.g., Fajnzylber *et al*., 2002; Buonanno and Leonida, 2009; Draca *et al.*, 2011).

With reference to Italy, the examination of the determinants of common crime has in recent years attracted the increasing attention of researchers. Scorcu and Cellini (1998), investigate the long run

[1] For a review of the theoretical and empirical economic literature of crime see Glaeser, 1999, Fajnzylber *et al.* (1999), and Buonanno (2003).

relationship between economic determinants and crime rates in Italy over the period 1951 to 1994. Their main conclusion is that homicides and robbery rates are explained by the level of real per capita consumption, while thefts are better predicted by the unemployment rate. Marselli and Vannini (1997) consider the determinants of four different crimes (i.e., murder, theft, robbery, and fraud), finding that in deterring crimes the probability of punishment is relatively more effective than the severity of punishment and the efficiency of police. Among the variables representing the opportunity cost of participating in illegal activities, the unemployment rate encourages homicides and robberies, but discourages thefts. Buonanno (2005), using regional data, also finds that unemployment has a large and positive effect on every classification of crime. More recently, Buonanno and Leonida (2009) by using a panel data set for Italian regions over the period 1980-1995, find that education reduces crime through better labor market opportunities (employment rate and wage rate). Further, Bianchi *et al.* (2012) investigate the relationship between immigration and crime across Italian provinces and show that the size of the immigrant population contributes to both the incidence of property crime and to the overall crime rate.

The theoretical literature on crime has also examined factors contributing to a distinctive type of crime, organized crime. According to this line of work, a criminal organization is modeled either as a monopolistic firm or as a centralized quasi-government. The former branch of the literature is based on industrial organization aspects, stressing that monopoly in the supply of illegal activities is socially desirable (see Buchanan, 1973; Garoupa, 2000). In the latter branch of the literature, a criminal organization is seen as competing or colluding with the State to monopolize a particular market, such as the market of property rights protection and of contract enforcement (see Shelling, 1984; Konrad and Skaperdas, 1998; Alexeev *et al.*, 2004).

More recent theoretical studies have focused on the optimal law enforcement that deters criminal coalitions. Chang *et al.* (2005) endogenize the size of a criminal organization and allow soldiers' commissions to depend on criminal abilities, which, in turn, affect the optimal law enforcement.[2] Mansour *et al.* (2006) endogenize the formation of gangs in a model in which the criminal market

[2] Their model assumes that the criminal organization is a franchise in which members have to pay an entry fee in exchange for Mafia's benefits (in terms of higher influence, better business, and lower probability of deterrence). The entry fee is endogenously determined and equal for all members. In equilibrium, a higher entry fee discourages potential offenders from committing crime (especially those with low skills and low commission), so that the government can save on the law enforcement budget given a tolerable crime rate.

structure reacts to deterrence. Assuming that larger gangs are an easier target for enforcement authorities than smaller gangs, the authors show that an increase in deterrence may lead to a splintering of cartels. Thus, by increasing the number of criminal organizations in the market, increased deterrence leads to an increase in output and to a fall in prices, consistent with the findings of having a more competitive market structure. In Garoupa (2007), severe punishment reduces the dimension of a criminal network, while, at the same time, it might increase the effectiveness of its members. The reasoning is that as fewer mistakes are committed in smaller firms (criminal networks) given they are easier to manage, a more severe penalty decreases the size of criminal organizations but also decreases the probability of detection. Consequently, less severe law enforcement leads to optimal deterrence of OC.

The most relevant theoretical work for our study is the recent paper by Chang *et al.* (2013) that examines both individual and organized criminal behavior in a general equilibrium framework. Specifically, the authors model, on the one hand, choices between legal and illegal activities, and on the other, the choices between two types of illegal activities: normal crime vs. organized crime. In this way, they complement conventional studies by highlighting the role of the occupational choice mechanism in understanding different criminal activity outcomes on the overall crime rate and the composition of crimes (between normal and organized). In equilibrium, criminals of normal crime and of organized crime face different risks of arrest, success rates, reward structures, as well as different outside options. Their findings show that a higher arrest rate raises the probability of dismantling a gang, pushing its members toward normal crime, thus raising the population of individual criminals (substitution effect). They also show that organized criminal activities are less responsive to formal labor market conditions than individual criminal activities. As a result, in response to better labor-market conditions (for instance, a higher job finding rate), although the overall crime rate falls, the composition of crime changes due to a higher ratio of organized to individual criminals.

The studies that empirically examine the determinants of OC are limited at both the single- and cross-country levels. This is principally due to the lack of reliable data and of good measures of the phenomenon. Milhaupt and West (2000), for example, provide empirical support for the claim that organized crime competes with the state to provide property rights enforcement and protection services. Based on time series data from Japan, the study shows that the structure and activities of organized criminal firms are significantly shaped by State-supplied institutions: as persons turn to State intermediaries for services, such as dispute settlement, bankruptcy, real estate foreclosures, and financing, the size of OC declines. Frye and Zhuravskaya (2000), instead, test the hypothesis according to which higher levels of regulation is associated with a greater reliance on the racket (criminal organizations) to protect property rights and enforce contracts. By using data from a survey of 230 small shops in three Russian cities (Moscow, Ulyanovsk, Smolensk), they find evidence that a higher level of government regulation raises the probability of contact between shopkeepers and private protection rackets.

At the cross-country level, Sung (2004) evaluates two hypotheses of predatory organized crime, the State failure hypothesis and the economic failure hypothesis. The first hypothesis argues that the failure of the State in the delivery of basic political goods such as security, justice, and institutional stability encourages criminal groups to perform state functions. The second hypothesis holds that poor economic outcomes, such as high unemployment, low standards of living, and a reliance on an underground economy, stimulates the growth of criminal syndicates as suppliers of demanded goods, services and jobs. Results, based on a panel data of 59 countries over the period 1999-2000, provide general support to both hypotheses, citing both types of failures as important elements of an organized crime-infested society.

Specific to the case of Italy, it is important to note that there exist a few empirical studies that focus on the origins of the Sicilian Mafia by stressing its role in substituting the State in the provision of security and the enforcement of property rights (Bandiera, 2003), or by being a product of the interaction between natural resource abundance, specifically sulfur and citrus fruits, and weak institutions (Buonanno *et al.* 2012). These studies, however, concentrate on the historical origins of the Mafia in specific areas of Italy, rather than on the current-day determinants of OC. Although such work is important for understanding how the phenomenon first emerged, it does not explain its persistence or its spread to other Italian regions.

The current study differs from this branch of the literature because it investigates the current economic, demographic and deterrence determinants of OC and compares them to the drivers of normal criminal activities. Specifically, we investigate the driving forces of both individual and organized crime for

Italy over the period 1983-2003, and compare whether these drivers differ across the two types of crime. In this way, we offer an analysis that jointly considers the factors that influence both forms of organized and normal crime in Italy. From a policy perspective, the results have implications about the formulation of law enforcement interventions that would most effectively address each type of crime in the most cost-effective manner.

In general, our results corroborate the theoretical predictions of studies that examine the determinants of both organized and common crimes. We show that the crime-deterrence variables and the share of economically active population affect in the same negative way both organized and common crimes. Some of the other drivers, instead, influence only organized crime, namely higher levels of education and of population density, associated with higher rates of the phenomenon. This leaves little doubt, in the fight against both types of criminal activities, about the importance of law enforcement policies and legal labour market opportunities.

The rest of the paper proceeds as follows. Section 2 describes the estimation strategy and method employed in our empirical analysis. Section 3 describes the data. Section 4 reports the benchmark results, while section 5 applies a number of robustness tests. Finally, section 6 concludes the paper with a summary and some final remarks.

## 2. Estimation Strategy and Method

The aim of our investigation is to test the main drivers of both organized and normal crime and examine the extent to which they may differ. According to the economic model of crime by Becker (1968), criminals are rational individuals who assess the risk of apprehension and punishment prior to committing an offence, and ultimately evaluate the expected benefits and costs associated with an illegal activity. We follow this approach for both types of crime, which is summarized by the following regression specification:

$$c_{i,t} = \alpha + \sum_{j=1}^{m} \gamma_j X_{j,it} + \mu_i + \varepsilon_{i,t}. \qquad (1)$$

In equation (1), the dependent variable $c$ is a measure of crime, organized or individual, in region $i$

during period *t*; *X* represents a vector of explanatory variables typically included in crime regressions (demographic, socio-economic, and deterrence);[3] $\mu$ captures unobserved time-invariant region-specific effects; and $\varepsilon$ is the time-varying error term.[4]

Starting with the control variables, the set of socio-economic and demographic variables included in the baseline regression is the following: logarithm of per capita GDP, growth rate of per capita GDP, share of active population, secondary school enrollment rate, and the rate of population density. In addition to these baseline variables, an extended group of controls includes the ratio of trade to GDP, the share of total public spending to GDP, a measure of financial development, and the sex ratio. Amongst the baseline explanatory variables, we also include two crime-deterrence variables that proxy for the efficiency of the police in deterring crime represented by (i) the ratio of crimes committed by unknown offenders to all recorded crimes in a given category of crime and (ii) the ratio of arrested offenders to the total number of recorded crimes in a given category of crime.

The two deterrence variables are considered in order to measure the risk of apprehension and punishment, which represent costs in committing crime. Thus, they are expected to reduce crime (see Imrohroglu *et al.* 2006; Neanidis and Papadopoulou, 2013). The logarithm of per capita GDP and the growth rate of per capita GDP are both included as indicators of legal income opportunities, which can either increase the opportunity cost of committing crime, and thus lower crime, or attract more criminal behavior as the expected gains from crime rise, and thus increase crime. So, ex ante these two variables have an ambiguous effect (see Marselli and Vannini, 1997; Kelaher and Sarafidis, 2011). The share of the economically active population is included to consider labour market opportunities, typically captured by the employment rate or the average wage. Our choice is due to the lack of data on unemployment rates and average wages for the period under consideration. The literature has identified this variable to be negatively associated with crime (see Ehrlich, 1973, Witt, 1998; Fajnzylber *et al.*, 2002). A further factor that has received considerable attention in the crime literature, related to the effect of economic conditions on crime, is the level of education of the population which raises the expected rewards from legal activities (see Lochner, 1999; Buonanno and Leonida, 2009). Finally, we include as control the density of the population, found to be a contributing factor to crime due to

[3] For more details, see Buonanno (2003) and Dills *et al.* (2008). The last study offers a review of the empirical literature on the determinants of crime.

[4] The definition of all variables, along with their sources, can be found in Table 1.

offering greater opportunities for criminals to find potential victims of crime (see Gleaser and Sacerdote, 1999; Bianchi *et al.*, 2012).

The main purpose of our investigation is to identify the main drivers of OC and examine whether they considerably differ from other categories of common crime. With this objective in mind, equation (1) is estimated by using both measures of OC and of individual crimes as a dependent variable. Following the literature, in order to avoid under-reporting bias, the main measure of common crime we consider is the rate of committed intentional homicides (per 100,000 inhabitants). We do, however, also consider other types of individual crime, such as thefts, robberies, and frauds.

Turning to discuss the main measure of OC we use as dependent variable, we follow the existing literature (see Daniele, 2009; Daniele and Marani, 2010; Pinotti, 2011; Blackburn *et al.*, 2014). This amounts to constructing different indexes of OC by considering various combinations of "mafia-related" crimes that we use throughout the analysis.[5] Our preferred measure of OC, however, is an index built as the sum of five different crimes that by definition reflect the presence of criminal organizations (coined OC Index 5):[6] (i) criminal association (art. 416 Italian Penal Code), (ii) Mafia criminal association (art. 416 bis Italian Penal Code), (iii) homicides by Mafia, (iv) extortion, and (v) bomb attacks. What follows is a summary of the explanation of our main OC index.

Since 1982, the Italian judicial system makes a clear distinction between criminal association (art. 416) and criminal association of Mafia-type (art. 416 bis).[7] Common criminal association is defined as "the association of three or more people who are organized in order to commit a plurality of crimes."[8] On the other hand, an association is defined of the Mafia-type "when its components use intimidation, awe

5 The term Mafia is used to include all the main criminal organizations that are present in the different Italian regions, such as Cosa Nostra in Sicily, Camorra in Campania, N'drangheta in Calabria, and Sacra Corona Unita in Puglia.

6 In fact, even if it is not always possible to distinguish crimes committed by the Mafia or other criminal organizations, from those committed by other criminals, it is possible to recognize that some offences are not typical of Mafia-type groups, such as crimes of fraud, theft and sexual violence, as underlined by Daniele and Marani (2010).

7 Until 1982, Article 416 of the Italian Penal Code ("associazione a delinquere") punished in the same way all groups of three or more people involved in some type of criminal activity. This generic term could not distinguish between small groups of bank-robbers and larger criminal networks with a powerful control over the territory. This changed in 1982 with the introduction of the crime: "associazione a delinquere di stampo mafioso" provided by Article 416 -bis (Law 646/82).

8 The characteristics of this kind of offence are the following: (i) the stability of the agreement among the components, i.e., the existence of an associative connection intended to be continuous through time even after once the crimes have been committed, and (ii) the existence of a programme of delinquency to commit an indeterminate number of crimes.

and silence (omertà) in order to commit crimes, to acquire the control or the management of business activities (i.e., concessions, permissions, public contracts or other public services), to derive profit or advantages for themselves or others, to limit the freedom of exerting the right to vote, and to find votes for themselves or others during an electoral campaign."

In general, all judicial-based measures of crime are subject to under-reporting, and this may be especially true for mafia-related crimes, as intimidation and silence (*omertà*) affect judicial investigations particularly in regions where criminal organizations are stronger. For this reason, given that under-reporting is smaller for crimes like homicides (Fajnzylber *et al*., 2002 and Soares, 2004), we include in our baseline index the number of homicides attributable to Cosa Nostra, Camorra, 'Ndrangheta, and Sacra Corona Unita.

Another usual crime of the Mafia-type organizations, which we incorporate in our baseline measure of OC, is extortion. In fact, it has been largely documented by the existing literature that almost all Mafia families exercise their power over a territory through the racket of extortion.[9] Also in this case, however, official data often underestimate the phenomenon, since the crimes formally reported to the police are less than those actually committed.[10] Since we have good reasons to believe that official data may underestimate the effective extent of extortion, we include in our OC index another crime which is symptomatic of the presence of the phenomenon, bomb attacks. Most of the times, bomb attacks are used to threaten and intimidate businessmen who refuse to pay extortion, or politicians who refuse to collaborate. These offenses, however, differently from those of extortion, cannot be hidden by the victims, so that they contribute to better capture the intensity of the phenomenon of extortion and of Mafia-type criminal organizations in general.

As mentioned earlier, the sum of these five mafia-related crimes composes our baseline OC proxy (OC Index 5). But to test the robustness of our benchmark findings, we build a variety of other OC indexes which also include the crimes of arson, "serious" robberies (i.e., robberies in banks and post offices),

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9 See, for example, Gambetta (1993) with reference to Cosa Nostra, Ciconte (1992) for N'drangheta, and Monzini (1999) for Camorra.

10 This has been regularly pointed out by Confesercenti (2009), according to which in the year 2009 a total of 160,000 commercial activities mainly based in Sicily, Campania, Puglia and Calabria have been subject to extortion, with total revenues estimated to be close to nine billions of Euros.

and kidnappings.[11]

We estimate Equation (1) with a variety of econometric procedures. We first employ the simple Ordinary Least Square estimator, which does not account for fixed effects or potential endogeneity of the explanatory variables. It is well-known, however, that in the presence of unobserved time-invariant region-specific effects and in the presence of endogeneity, the OLS estimates are biased and inconsistent. Given that the existence of region-specific factors is well recognized in the crime literature, we use the within group (fixed effects) estimator to control for these unobserved region-specific effects. But this methodology also ignores potential reverse effects that crime may exhibit on law enforcement policies and the other control variables. For this reason, our main estimation procedure is based on techniques that address potential endogeneity of the right-hand side variables, in the form of system-GMM regressions. This dynamic panel technique has already been used in the empirical crime literature by a number of studies (e.g., Fajnzylber *et al*., 2002; Buonanno, 2005; Neanidis and Papadopoulou, 2013).

The system-GMM estimation seems to be appropriate since it is based on techniques that control for (i) potential endogeneity of the regressors, (ii) region-specific effects, and (iii) heteroskedasticity and autocorrelation within regions. Specifically, the system-GMM estimation, developed by Arellano and Bover (1995) and Blundell and Bond (1998), accounts for possible endogeneity by treating the model as a system of equations in first-differences and in levels. The endogenous variables in the first-difference equation are instrumented with the lags of their levels, whilst the endogenous variables in the level equation are instrumented with the lags of their first differences. An advantage of this GMM estimator is that it avoids a full specification of the serial correlation and heteroskedasticity properties of the error, or any other distributional assumption.

An important consideration associated with dynamic GMM estimators relates to the number of used instruments. According to Roodman (2009), an excessive number of instruments can lead to over-

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[11] Crimes of arson are considered because, as well as crimes of bomb attacks, they are indicative of the presence of extortion and of a more general intimidating activity of criminal groups. Robberies in banks and post offices, instead, are included since they are often related to OC as they require a high degree of organization and the collaboration of a plurality of individuals. Finally, the inclusion of crimes of kidnapping is due to the fact that "historical" Mafias have specialized through time in this kind of offense, as also recognized by previous studies (e.g., Ciconte, 1992; Pinotti, 2011).

fitting of the instrumented variables, consequently biasing the results towards those obtained by the OLS estimator. In order to keep the number of instruments low, given the small number of Italian regions, we use a lag structure of two to four lags and we always collapse the instrument set.[12] Notice that the number of instruments is high because we treat all the explanatory variables in our benchmark model as endogenous, with the only exception of the rate of population density. Of particular importance is the fact that reverse causality between crime and its deterrence measures is present in the data by construction since the numerator of the dependent variable (number of all recorded crimes) is also the denominator in the fraction of crimes committed by unknown and in the probability of being arrested. This artificially induces a negative correlation between the variables, a phenomenon known in the literature as "ratio bias" (see e.g. Dills *et al*. 2008). In addition, we treat the logarithm and growth rate of GDP per capita, the share of active population and the level of education as endogenous, since crime has a direct effect on economic activity and thereby on legal employment opportunities.

Finally, in the system-GMM estimations, we test the validity of the instruments by applying two specification tests. The first is the Hansen (1982) *J*-test of over-identifying restrictions which we use to examine the coherency of the instruments. The second is the Arellano and Bond (1991) test for serial correlation of the disturbances up to second order. This test is important since the presence of serial correlation can cause a bias to both the estimated coefficients and standard errors. We use robust standard errors, which are valid under arbitrary forms of heteroskedasticity and serial correlation. We also perform the correction proposed by Windmeijer (2005) for the finite-sample bias of the standard errors of the two-step GMM estimator.

## 3. Data

The choice of carrying out our analysis at a cross-regional level for the case of Italy rather than at a cross-country level is mainly due to the availability of data on crimes ascribable to organized criminal groups. The Italian National Institute of Statistics (ISTAT) offers a variety of data on mafia-related crimes which are available for a relatively long period; this has allowed us to build a variety of indexes and to carry out our investigation for an adequate length of time. Given the lack of appropriate and reliable data on organized crime at an international level, such an analysis would not have been possible at a cross-country level.

[12] In large samples, collapse reduces statistical efficiency; but in small samples, it can avoid the bias that arises as the number of instruments climbs toward the number of observations (Roodman, 2006).

We use a panel of 19 Italian regions over the period 1983-2003, giving a maximum number of 399 observations.[13] All our regressions use 380 observations, utilizing 95% of the maximum data. The only exception is for a measure of OC (OC Index CRENoS) for which 304 observations are available due to a shorter time period coverage. Table 1 provides definitions, sources and the exact period availability of the data, while Table 2 presents summary statistics. Figure A offers a time series illustration of the OC Index 5 and of the rate of intentional homicides committed, by region. Evidently, some regions have higher levels of OC than others and these are the regions that exhibit most of the variability in the data (Basilicata, Calabria, Campania, Puglia, Sardegna, Sicilia). For these regions, a similar pattern seems to be followed by homicide rates, albeit lower in absolute levels. Despite this, a strong positive association between the two types of crime is not clearly observable, as indicated by a correlation coefficient of 0.5. Thus, one cannot claim from the outset that the two types of crime are driven by the same factors. To examine this, we next turn to a formal empirical investigation.

## 4. Baseline Results

We begin our analysis by estimating equation (1) first with simple OLS, then with fixed effects to account for region-specific differences in crime, and finally with system-GMM to also account for the potential endogeneity of the right-hand-side variables. These baseline findings are reported in Table 3, where the first three columns show the results obtained by using as dependent variable our main measure of OC (OC Index 5), while the following three columns refer to the results obtained by using the rate of committed intentional homicides, our primary measure of common crime. In what follows, we discuss the baseline results based on the system-GMM estimation method due to its advantages compared to both OLS and FE.

We first consider the two deterrence variables (unknown and arrested), which proxy for the effectiveness of the police and for the risk of apprehension, which, in turn, can be thought as reflecting the costs of committing crime. It is reasonable to expect that an increase in the probability of being arrested reduces the amount of crime because it increases the expected costs associated with criminal activity and, therefore, reduces the expected gains from crime. In the same way, the more inefficient the

[13] We exclude the region of Valle d'Aosta because it is the smallest and richest region, usually excluded in empirical analysis of Italian regions being treated as an outlier.

police is in deterring crime (higher unknown), the higher the incentive to commit crime, or be involved in some criminal coalition, since the probability of being apprehended is lower. As a result, we expect the coefficients of unknown and arrested to be positive and negative respectively, which is exactly what we observe in column 3. Earlier empirical studies on the determinants of OC, instead, have found mixed results with regard to the impact of deterrence variables. Milhaupt and West (2000), for example, find that the size of gangs (as measured by membership) in Japan is positively correlated to the firm member arrest rate. The authors give several explanations for this counter-intuitive result.[14] At the same time, however, the study finds that enforcement of the Anti-Organized Crime Act has reduced the success of organized criminal firms, lending support to more targeted policing interventions in combating OC. Closer to our study, Caruso (2009) finds that in Italy higher public spending toward the protection of the population reduces OC. Even though public expenditure for enforcement purposes does not directly capture the effectiveness of the police, one can assume that higher policing expenditure can raise the effectiveness of the law enforcement agencies, thus, reducing OC. In this way, then, our findings corroborate Caruso (2009). Our empirical results also confirm the theoretical predictions of Chang *et al*. (2013), who establish that a tighter crime deterrence policy, in the form of either an arrest rate or non-pecuniary punishment, reduces the amount of organized crime.

Turning to the other control variables, the level and the growth rate of per capita GDP, both included to capture the level of prosperity and economic activity in the regions, are usually found to have a negative effect on crime (Fleisher, 1966; Ehrlich, 1973). The negative effects of economic activity on crime are related to the legal income opportunities created through higher income and economic growth. As both these variables represent the expected gains of legal activities, their higher values decrease illegal activities as the opportunity cost of committing crime increases. However, some studies have identified a positive effect of economic activity on crimes, especially property crimes. The rationale being that in more prosperous economies, the expected gains from crime increase. This can equally apply with reference to OC, where criminal organizations expand their business to more affluent areas. Indeed, Pinotti (2011) has shown that organized criminal activities in Italy have been spreading to the Northern, and wealthier, part of the country. Thus, ex ante the effect of economic

[14] The positive correlation may be due to a community crackdown (i.e., police must arrest a greater percentage of members as organizations grow larger and more visible), a replacement phenomenon (i.e., perhaps more than one new member is needed to replace every jailed experienced member), or even a data-gathering quirk (i.e., new members might replace members who are in prison, but prisoner-members remain on the firms' membership lists).

activity on OC is not clear, even though both the theoretical predictions by Chang *et al*. (2013) and the empirical fidings by Buscaglia and Van Dijk (2003) support a negative effect. Our results, however, show that economic activity, proxied by economic growth, enhances OC. This outcome supports the argument that criminal organizations infiltrate in areas with high economic activity where greater opportunities of profitable business are possible.

The active population rate, by proxying for legal labour market opportunities, is expected to lower the level of crime. As argued by Buscaglia and Van Dijk (2003), in many cases unemployment not only provides a greater supply of potential illegal labor for organized criminal activities, but also creates a favorable environment for criminals to exploit the social fabric of countries as a foundation for OC. In other words, joblessness can turn criminal organizations into major employers. This prediction is echoed in our findings where a higher active population share reduces OC. It is also consistent with the theoretical result of Chang *et al*. (2013) where improved formal labour market conditions (captured by a higher job finding rate) reduce the fraction of people employed by criminal organizations.

Another demographic variable that receives attention is population density. Studies that support the hypothesis of a positive link between population density and crime cite three theories: (i) the theory of overcrowding and anti-social behavior (e.g., Lorenz, 1967), (ii) the theory of association between population density and poverty (e.g., Curtis, 1975), and (iii) the theory of increased opportunity for crimes in densely populated areas (e.g., Harries, 1974). Studies that hypothesize a negative link between crime and population density (e.g., Shichor *et al.* 1980) typically do so based on Jacobs (1961)' theory, which states that crowded streets work to inhibit the occurrence of crime. According to this explanation, the informal neighborhood surveillance prevents crimes from occurring. Most recent studies, however, seem to confirm that there is more crime in more populated areas than in less populated or rural areas (Glaeser and Sacerdote, 1999; Buonanno, 2005, for the case of Italy). Importantly, one of the few empirical studies on the determinants of OC that has considered this variable, Osorio (2011), found that the number of confrontantions between rival criminal organizations as well as against the State in Mexico is higher in large municipalities. Our finding also points to a positive effect of population density on OC, albeit at the 10% level, largely confirming the empirical literature.

The last socioeconomic variable is the level of education, which determines the expected rewards from both legal and criminal activities (Lochner, 1999; Buonanno and Leonida, 2009). Specifically, most of the contributions on the effects of education on crime focus on how education raises individuals' skills and abilities, thus increasing both the expected returns to legitimate work and the opportunity costs of illegal behavior. There also exists an indirect (non-market) effect of education that affects the preferences of individuals. This effect, the so-called "civilization effect", makes criminal decisions more costly in psychological terms (Usher, 1997). Witte and Tauchen (1994) also suggest that school enrollment alone, independently of the level of schooling, by reducing the time available for getting involved in crime activity, leads to a decrease in the crime rate.

According to these theories and the related empirical studies, criminals tend to be less educated and from poorer economic backgrounds than non-criminals (Gleaser and Sacerdote, 1995). If the same argument applies to the choice of joining a criminal organization, we would expect more education to diminish OC. Our results, however, support a positive impact of education on OC. This result is not counter-intuitive if one considers that organized criminal organizations need to recruit educated individuals in order to survive and develop in an ever dynamic environment both with regard to the way they formulate their business strategies and by the way they keep them secret from law enforcement agencies. This finding is also supported by Chang *et al.* (2013), who show that labour market policies aimed at improving labour market opportunities, such as incentives for further education, increase the extent of OC due to the presence of a risk-sharing effect associated with organized crimes.[15] Furthermore, a positive effect of education has also been found for other types of crime, such as for property crimes in the USA (Ehrlich, 1975) and for total crimes in Italy (Buonanno, 2005).[16]

Having described above the drivers of OC, the last column of Table 3 presents results with regard to non-organized crime, by using the rate of committed intentional homicides. In this case, the variables

[15] This risk-sharing effect captures the insurance the criminal organization offers to each member by which it pays them a commission for undertaking an illegal project even in the event of being arrested.

[16] Ehrlich (1975) gives four possible explanations for this puzzling empirical finding. First, it is possible that education may raise the marginal product of labour in the crime industry to a greater extent than for legitimate economic pursuits. Second, higher average levels of education may be associated with less under-reporting of crimes. Third, it is possible that education indicators act as a "surrogate for the average permanent income in the population, thus reflecting potential gains from crime, especially property crimes". Finally, combined with the observation that income inequality raises crime rates, it is possible to infer that certain crime rates are "directly related to inequalities in schooling."

that determine crime are the two deterrence variables and the growth rate of GDP per capita. Specifically, we find that intentional homicides respond positively to the inefficiency of the police in "clearing-up" crimes and negatively to the apprehension rate. Both these findings are consistent with the related literature and with those established above for OC. Turning to the socio-economic variables, only economic activity is found to be significant and, in contrast to the case of OC, taking up a negative sign. This implies that growth spurts in Italian regions drive out individual criminal activity due to better labour market opportunities, but attract OC activities due to the greater opportunities created for them to appropriate part of the generated higher income. Our results as to the drivers of homicide rates are generally in line with the empirical literature of common crimes in Italy, where the remaining controls do not contribute to crime (e.g., Marselli and Vannini, 1997, Buonanno, 2005).

With regard to instrumentation, the specification tests in Table 3 corroborate the validity of the instruments. Hansen's J-statistic cannot reject the hypothesis that the instruments are uncorrelated with the error term at a standard confidence level. Additionally, the Arellano and Bond (1991) test cannot reject the hypothesis of no second-order serial correlation in the error term in all regressions at any conventional level of significance.

## 5. Robustness checks

This section tests the robustness of our baseline findings under different modifications that include (i) different model specifications, (ii) alternative measures of OC, and (iii) different types of individual crime. In all cases the benchmark findings are not overturned.

### 5.1 Robustness to the inclusion of additional controls

We first check the robustness of our main results by adding, one at a time, additional control variables that usually appear in the economic model of crime. These variables are the ratio of trade to GDP, the share of total public spending to GDP, a measure of financial development, and the sex ratio. The results for OC are reported in Table 4, where we observe that our baseline results remain in tact, with most of the additional variables being statistically significant and with the expected sign.

In a cross-country analysis, Buscaglia and Van Dijk (2003) find the degree of a country's openness (expressed by the extent of regulations applied to foreign trade and openness to imports and foreign direct investment) to be inversely related to OC. They claim that openness "…is important in permitting new economic forces to challenge incumbents within domestic markets and to undermine the old economic capture of a territory by organized crime." On the basis of this argument, we would expect the coefficient of trade in our regression to be negative. In contrast, we find the degree of a region's openness raising OC. A plausible explanation of this result is summarized by the UNODC (2010), stating that "…the same conditions that have led to unprecedented openness in trade have created massive opportunities for criminals. As a result, organized crime has diversified, gone global, and reached macro-economic proportions." This further emphasizes the point that criminal organizations operate at a global scale, with activities in drug trafficking, money laundering and prostitution, so that a region's openness offers further opportunities for the pursuit of such objectives.

Next, we find the impact of public spending on OC to be positive. This result does not come as surprise as it has already been established in the literature and it is well recognized that criminal organizations are particularly interested in the appropriation of public money ("…more than one fifth of Mafia's profits come from public investment," Giovanni Falcone in Cose di Cosa Nostra, 1991). Caruso (2009), for example, finds that in Italy the size of criminal organizations is positively associated to public spending and public investment. Similarly, Gennaioli and Onorato (2010) use Italian data to evaluate the spread of OC caused by an increase in public funding which followed an earthquake affecting two regions in the center of Italy (Marche and Umbria) in 1997. Results show an increase in the diffusion of OC in those provinces hit by the earthquake. In line with this reasoning, Barone and Narciso (2011) also argue that funding policies should take into account the risk that at least part of the money feeds into OC. According to their analysis, conducted at a municipality level for Italy, the presence of OC positively affects both the extensive margin (probability of obtaining funding) and the intensive margin (amount of public funds to enterprises) of public funding.[17]

Controlling for financial development in column 4, reveals its negative effect (at the 10% level) on OC. This result corroborates the hypothesis that criminal organizations are more likely to operate in regions

[17] An example comes from the European Structural Funds, one of the main policy instruments used to stimulate convergence across European states. According to a report by the Commission of the European Communities (2008), the number of irregularities related to European Structural Funds was 4,007 in 2008, an increase of 6.7% compared to 2007. Although there are no official statistics for EU fraud involving Mafia activity, the European Parliament warns of the role of OC, which "[...] is increasing its capacity for collusion within institutions, particularly by means of fraud against the Community budget." More recently, the legislative proposals regarding the EU cohesion policy 2014-2020 stress the role of institutions and the quality of government in assigning funds.

where access to credit is more difficult, a phenomenon pronounced since the onset of the financial crisis (Bank of Italy, 2010). This is further supported by Confesercenti (2009), which reports that the Mafia's fastest growing activity is usury, registering a boom in the year 2009 as a direct consequence of the financial crisis and the accompanied credit crunch. The studies of Buscaglia and Van Dijk (2003) at the cross country level and Milhaupt and West (2000) for Japan, reveal similar findings where a less transparent and effective banking system by making it more difficult for businesses to access financial services within the formal regulatory framework, forces them to rely on illegal sources for the provision of financial services at higher interest rates.

The last extra control variable we examine in this section is the ratio of male to female population. Males can be thought of as being more prone in engaging in criminal activities than females as considered by Marselli and Vannini (1997) and Freeman (1991), which within our framework could be sensible given that men have historically played the principal role in the Mafias. If so, then we would expect the coefficient of sex ratio to be positive. This is not the case, however, as the coefficient is not found to be statistically significant, suggesting that the population's gender composition does not influence the level of OC in Italian regions. This finding is in line with Confesercenti (2009), which reports that the gender composition of criminal organizations in Italy has been changing over the last few decades, with an increasing number of women being involved. According to the figures, however, the Mafia still remains an organization dominated by males.[18]

Finally, we check the robustness of our baseline findings with regard to homicide rates. Table 5 displays the results obtained by adding the same extra controls as in the OC regression. Once again, our main findings remain in place, with the homicide rate now also being positively affected by public expenditure and negatively affected by financial development, as in the case of OC. Similarly, the gender composition of the population plays no role in homicides rates, while now trade openness does not influence this type of crime.

### 5.2 Robustness to alternative measures of organized crime

In the analysis presented above, we have estimated the OC model by using our preferred measure of

[18] An alternative, or even complementary, explanation of why gender composition does not affect OC has been underlined by Marselli and Vannini (1997) in their empirical analysis of the determinants of crime in Italy: the very small variability of the ratio across regions over the sample period.

OC Index 5 as the dependent variable. We now proceed to test the robustness of the baseline results by employing alternative measures of OC. The literature has proposed different indexes to proxy for the presence of criminal organizations, so it is important to verify that our results can be established with the use of these measures. For this reason, we construct additional OC measures by considering different combinations of "mafia-related" crimes and use them alternatively. The results are reported in Table 6.

Column (1) replicates column (3) of Table 3 for comparison. As largely discussed in Section 2, the baseline measure of OC is built as the sum of official data recording five different crimes that by definition reflect the presence of criminal organizations. Column (2), instead, reports the outcomes obtained by using an index that adds "kidnapping for extortion" to the baseline OC Index 5. The inclusion of the crime of kidnapping is due to the fact that "historical" Mafias have specialized through time in this kind of offense, as also recognized by Pinotti (2011). Further, the results reported in column (3) have been obtained by using a measure of OC which includes all crimes considered in OC Index 5 plus the crimes of kidnapping for extortion and arsons. The crime of arson, similarly to bomb attacks, is considered in order to proxy for an offense frequently used to intimidate businessmen unwilling to pay for extortion (see Confesercenti, 2009; Daniele and Marani, 2010). The last column of the table uses an index of OC built as the sum of crimes on "serious" robberies (in banks and post offices), kidnapping for extortion, and extortion, all available from CRENoS. The crimes of "serious" robberies are considered because they are often related to OC given that they require a high degree of organization and the collaboration of a plurality of individuals. Illustrated in Table 5, in all cases, our main findings continue to be strongly supported and do not seem to be affected by the specific measure of OC adopted as dependent variable. The only exception refers to the two indicators of economic activity (level and growth rate of GDP per capita), which switch significance in columns 3 and 4. This, however, does not change in any way our earlier interpretations.

### 5.3 Robustness to different types of individual crime

The main measure of common crime we have considered thus far is the rate of intentional homicides. In this section, we study the determinants of other types of individual crime. Results are shown in Table 7, where column (1) replicates column (6) from Table 3 for comparison. Columns (2), (3) and (4) refer to the results obtained when using respectively thefts, robberies, and frauds as our crime indicator. Note that it is not expected the drivers of these other types of individual crime to be the same as those of homicides, as the incentives behind life-threatening crimes and property crimes can differ.

In column 2, thefts are shown to be positively related to economic activity as proxied by GDP per capita. This is a typical finding in the literature of property crimes and contrary to the findings of homicide rates (for Italy, see Scorcu and Cellini, 1998, and Buonanno, 2006). As pointed out by Field (1990), this finding is mainly due to two effects: an opportunity effect and a lifestyle effect. According to the opportunity effect, with business booming and consumption growing, opportunities and returns for crime increase simultaneously, with both the number and the value of goods. The lifestyle effect, instead, argues that economic development induces a change in routine activities in a direction that favors potential criminals. Active population exerts a negative effect on thefts as previously found in crime regressions for the case of Italy (i.e., Marselli and Vannini, 1997 and Buonanno, 2005), while education is now also significantly deterring thievery activity. The rest of the control variables are not statistically significant, including the two direct deterrence variables.

The results for robberies reported in column 3 are similar to those of thefts, not surprisingly given that both represent crimes on property (although robberies may involve a threat to life). As for thefts, robberies are positively related to economic activity and negatively related to the labour market active population. Now differently, education is not statistically significant and the deterrence variable of the "clearing-up" rate is taking up a positive sign. These last two results are consistent with those of homicides, due to the involvement of threat to life during robberies.

Finally, column 4 presents the findings for frauds. Given that this type of criminal activity is popular amongst white collar workers, known as white-collar crime, it is intuitively palatable that it subsides during periods of expansion in economic activity (higher level and growth of GDP per capita) when workers typically earn above their average salary. Thus, income gains from fraud and from labour market activities act as substitutes. Further, frauds are committed by people already participating in the labour market, so this type of crime increases with the share of active population, while the more educated the population, the higher the level of fraud. This positive link arises due to the need of having skills and knowledge, and thus a minimum level of education, to commit fraud successfully (Wheeler *et al.*, 1988; Benson and Moore, 1992). Finally, the higher the number of unresolved cases of fraud, the higher the instances of fraud given the ineffectiveness of law enforcement agencies. However, higher arrests of fraudsters do not deter fraud. To the contrary, they seem to encourage fraud, possibly because those engaged in fraud believe that the chances of being arrested are low.

Summarizing, the robustness section has shown that our baseline results for OC are not sensitive to the inclusion of additional control variables or the use of alternative measures of OC. But one cannot say the same thing with regard to common crimes, where findings vary for its different categories consistent with the literature.

## 6. **Conclusions**

The phenomenon of crime, in general, and of organized crime, in particular, represents an increasing threat to both economies and societies. For this reason, it is crucial to understanding the drivers of criminal behavior and the process by which criminal coalitions are formed as a first step in planning and implementing those policies that are necessary in reducing such activities. In this endeavour, it is of chief importance knowing whether common crime and organized crime are influenced by the same factors, and if so, by which ones. Such information can assist to the careful targeting of policing interventions in specific areas of criminal activities. This paper contributes to this objective by offering a comparative empirical analysis regarding the drivers of crime, both common and organized.

Since Becker (1968)'s seminal analytical contribution, many studies have investigated empirically the causal factors of crime. A few studies, however, have focused on the determinants of organized crime. The current study examines jointly the drivers of both individual and organized criminal behavior in the framework of Italy over the period 1983-2003. By examining a set of demographic, socio-economic, and deterrence variables, we seek to find whether there are common drivers in the variation (across time and regions) of both types of crime. Our results show that both types of crime respond symmetrically to some drivers, in that they are both reduced, by more efficient policing and a more economically active population (with the exception of frauds for the latter). But, there are also factors that are important only for one type of crime, where both a higher level of education and population density contribute to higher organized crime. These results are robust to a battery of sensitivity tests, including different measures of organized crime and model specifications.

Our findings seem to suggest that policymakers, in their fight against common and organized crimes, can benefit by directing public funds towards increasing the efficiency of the police and by tightening the law enforcement system. Similar benefits can arise by implementing policies that improve legal labour market opportunities, such as more and better quality of education and the availability of worker training programs. The analysis we have presented can be seen as a first step in the understanding of the drivers of organized crime and of their comparison with those of common crimes in Italy. Further valuable research could consider, on the basis of the recent work of Chang *et al.* (2013), the effects of labour-market improvement programs and of more effective crime-deterrence policies on the *composition* of crime (ratio of organized-to-individual criminals).

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## Table 1
## Description of Variables and Sources

| Variables | Description | Sources |
|---|---|---|
| **GDP per capita** | Log of GDP per capita in thousands of millions of lire *(constant prices 2000 euros)* | ISTAT- Annals of Statistics and CRENoS -1983/2003 |
| **GDP growth per capita** | Log difference of GDP per capita in thousands of millions of lire *(constant prices 2000 euros)* | ISTAT- Annals of Statistics and CRENoS-1983/2003 |
| **Education** | Percentage of population in age range 14-18 registered in high school | ISTAT- Annals of Statistics and CRENoS -1983/2003 |
| **Active Population** | Percentage of resident population actually employed or actively searching for a job | ISTAT- Annals of Statistics - 1983/2003 |
| **Population Density** | Resident population / regional surface in $km^2$ | ISTAT- Annals of Statistics - 1983/2003 |
| **Unknown** | Ratio of crimes committed by unknown to all recorded crimes in a given category of crime | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **Arrested** | Ratio of recorded offenders to all recorded crimes in a given category of crime | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **Public spending** | Share of total public spending (as % of GDP) | ISTAT- Annals of Statistics - 1983/2003 |
| **Trade** | Share of trade (as % of GDP) | ISTAT- Annals of Statistics - 1983/2003 |
| **Financial development** | Share of value added of financial and banking sector (as % of GDP) | ISTAT- Annals of Statistics and CRENoS --1983/2003 |
| **Sex ratio** | Ratio of male-to-female population | ISTAT- Annals of Statistics - 1983/2003 |
| **OC Index 5** | Sum of the following crimes: Mafia criminal association, homicides by Mafia, criminal association, bomb attacks, extortion (per 100,000 inhabitants) | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **Homicides** | Number of intentional homicides (per 100,000 inhabitants) | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **Serious robberies** | Number of robberies in banks, post offices, jewelries, bank vans, post vans, vans transporting precious goods (per 100,000 inhabitants) | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **Thefts** | Number of thefts (per 100 inhabitants) | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **Frauds** | Number of frauds (per 100 inhabitants) | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **Extortion** | Number of crimes of extortion denounced (per 100,000 inhabitants) | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **Criminal association *(art.416)*** | Number of crimes of criminal association (per 100,000 inhabitants) defined as: *"the association of three or more people who are organized in order to commit a plurality of crimes"* | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **Mafia criminal association *(art.416 bis)*** | Number of crimes of Mafia criminal association (per 100,000 inhabitants) defined as: *“the association is of the Mafia type when its components use intimidation, awe and silence in order to commit crimes, to acquire the control or the management of business activities (i.e., concessions, permissions, public contracts or other public services), to derive profit or advantages for themselves or others, to limit the freedom of exerting the right to vote, and to find votes for themselves or others during the electoral campaign.”* | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **Homicides by Mafia** | Number of homicides by mafia (per 100,000 inhabitants) | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **Bomb attacks** | Number of bomb attacks (per 100,000 inhabitants) | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **Arsons** | Number of arsons (per 100,000 inhabitants) | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **Robberies in banks** | Number of robberies in banks (per 100,000 inhabitants) | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **Robberies in post offices** | Number of robberies in post offices (per 100,000 inhabitants) | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **Kidnapping for extortion** | Number of kidnapping for extortion (per 100,000 inhabitants) | ISTAT- Annals of Judicial Statistics -1983/2003 |
| **OC Index CRENOS** | Sum of the following crimes: extortion, kidnapping for extortion, serious robberies (in banks and post offices) per 100,000 inhabitants | ISTAT- Annals of Statistics and CRENoS - 1983/1999 |

**Table 2**
**Summary Statistics**

| Variable | Mean | Std Dev | Min | Max | Obs |
|---|---|---|---|---|---|
| GDP p.c. (2000 euro) | 15218.01 | 4018.03 | 7641.47 | 23625.44 | 380 |
| GDP p.c. growth (%) | 0.02 | 0.02 | -0.04 | 0.09 | 380 |
| Active population | 0.40 | 0.07 | 0.28 | 0.54 | 380 |
| Population density | 1.81 | 1.01 | 0.59 | 4.18 | 380 |
| Education | 0.75 | 0.14 | 0.42 | 1.01 | 380 |
| Unknown_OC Index5 | 1.36 | 0.64 | 0.00 | 2.84 | 380 |
| Arrested_OC Index5 | 17.80 | 11.65 | 0.75 | 69.03 | 380 |
| Unknown_homicides | 0.38 | 0.22 | 0.00 | 1.67 | 380 |
| Arrested_homicides | 0.93 | 0.34 | 0.13 | 2.36 | 380 |
| Public spending (% GDP) | 0.21 | 0.05 | 0.12 | 0.34 | 380 |
| Trade (% GDP) | 0.26 | 0.17 | 0.00 | 0.86 | 380 |
| Financial dev (% GDP) | 0.21 | 0.03 | 0.15 | 0.29 | 380 |
| Sex ratio | 0.94 | 0.02 | 0.88 | 0.98 | 380 |
| OC Index 5 | 10.36 | 8.66 | 1.61 | 53.81 | 380 |
| Homicides | 4.15 | 3.44 | 0.42 | 23.51 | 380 |
| Serious Robberies | 5.47 | 2.82 | 0.30 | 15.08 | 380 |
| Thefts | 70617.22 | 68144.35 | 1664.00 | 377248.00 | 380 |
| Frauds | 2597.02 | 3991.71 | 24.00 | 44114.00 | 380 |
| Extortion | 5.06 | 3.17 | 0.69 | 18.00 | 380 |
| Criminal Association | 1.74 | 1.08 | 0.00 | 6.76 | 380 |
| Mafia Criminal Assoc | 0.32 | 0.56 | 0.00 | 3.53 | 380 |
| Homicides by Mafia | 0.35 | 0.98 | 0.00 | 7.95 | 380 |
| Bomb Attacks | 2.90 | 5.23 | 0.00 | 33.29 | 380 |
| Arsons | 15.27 | 11.72 | 1.52 | 56.55 | 380 |
| Robberies in Banks | 2.90 | 2.01 | 0.00 | 11.45 | 380 |
| Robberies in Posts | 1.30 | 1.21 | 0.00 | 9.60 | 380 |
| Kidnapping for extortion | 0.16 | 0.15 | 0.00 | 0.93 | 380 |
| OC Index CRENOS | 6.60 | 6.62 | 0.40 | 34.25 | 320 |

*Notes:* Data on GDP per capita , secondary school enrolment, trade, public spending, financial development, sex ratio and active population are from CRENoS and the Italian National Institute of Statistics (ISTAT), Annals of Statistics (various years). Data on crimes and deterrence are from ISTAT, Annals of Judicial Statistics (various years). The period of time considered for the averages depends on the availability of data (see Table 1 for a detailed description of the availability of data). All crime rates are per 100,000 inhabitants.

**Figure 1**
**Time series trend (1983-2003) of organized crime index and homicide rates in Italian regions**

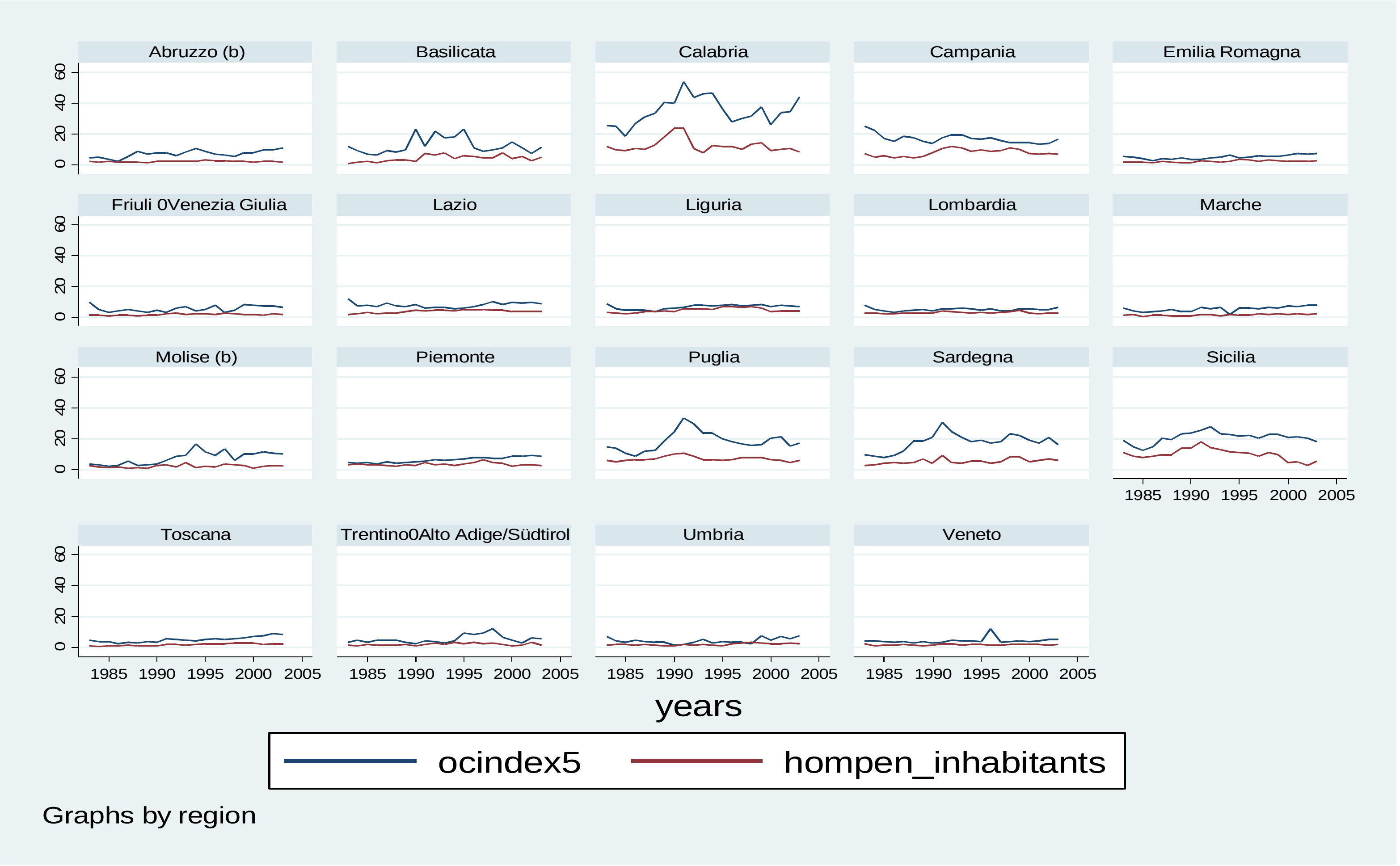

**Table 3**
**Benchmark Findings**

| | *Organized Crime (OC Index5)* | | | *Homicides rate* | | |
|---|---|---|---|---|---|---|
| | ***[1]*** | ***[2]*** | ***[3]*** | ***[4]*** | ***[5]*** | ***[6]*** |
| | ***OLS*** | ***FE*** | ***System-GMM*** | ***OLS*** | ***FE*** | ***System-GMM*** |
| **Log GDP per capita** | -9.47 | 2.53 | 1.54 | 2.01 | 6.69 | 2.24 |
| | *(0.021)* | *(0.648)* | *(0.848)* | *(0.296)* | *(0.010)* | *(0.490)* |
| **GDP pc growth** | -9.91 | -11.67 | 19.73 | -11.89 | -8.88 | -10.58 |
| | *(0.610)* | *(0.237)* | *(0.018)* | *(0.205)* | *(0.053)* | *(0.048)* |
| **Active population** | -32.28 | 5.25 | -87.84 | -34.68 | -15.45 | -16.61 |
| | *(0.021)* | *(0.761)* | *(0.005)* | *(0.000)* | *(0.063)* | *(0.235)* |
| **Education** | 11.92 | 7.73 | 17.60 | -2.51 | -3.91 | 0.28 |
| | *(0.000)* | *(0.094)* | *(0.007)* | *(0.058)* | *(0.064)* | *(0.897)* |
| **Unknown** | 5.75 | 1.08 | 2.03 | 4.65 | 2.49 | 2.63 |
| | *(0.000)* | *(0.013)* | *(0.012)* | *(0.001)* | *(0.000)* | *(0.000)* |
| **Arrested** | 0.08 | -0.02 | -0.03 | -0.71 | -0.55 | -1.21 |
| | *(0.008)* | *(0.205)* | *(0.083)* | *(0.148)* | *(0.092)* | *(0.032)* |
| Population density | -1.3 | -3.47 | 8.52 | 0.18 | 3.58 | 0.53 |
| | *(0.000)* | *(0.500)* | *(0.107)* | *(0.138)* | *(0.136)* | *(0.675)* |
| Regions/Obs | 19/380 | 19/380 | 19/380 | 19/380 | 19/380 | 19/380 |
| $R^2$ | 0.63 | 0.13 | | 0.59 | 0.19 | |
| Number of instruments | | | 25 | | | 25 |
| Hansen *J*-test (*p*-value) | | | 0.752 | | | 0.981 |
| AR(1) test (*p*-value) | | | 0.053 | | | 0.045 |
| AR(2) test (*p*-value) | | | 0.446 | | | 0.621 |
| No. of lags of endogenous variables used as instruments | | | (2 4) | | | (2 4) |

*Notes*: Dependent variable is the OC Index 5 (first three columns) and the rate of intentional homicides (last three columns). *p*-values in parentheses. Constant term not reported. Regressions based on OLS (Column 1 and 4), FE (Column 2 and 5), system-GMM (Column 3 and 6). Instrumented control variables are in bold type.

**Table 4**
**Robustness of Benchmark Findings for Organized Crime**
**(Additional Control Variables)**

| | **[1]** | **[2]** | **[3]** | **[4]** | **[5]** |
|---|---|---|---|---|---|
| **Log GDP per capita** | 1.54 | 16.94 | 5.53 | 9.68 | 15.67 |
| | *(0.848)* | *(0.135)* | *(0.561)* | *(0.316)* | *(0.347)* |
| **GDP pc growth** | 19.73 | 14.83 | 34.16 | 2.02 | 32.70 |
| | *(0.018)* | *(0.090)* | *(0.000)* | *(0.882)* | *(0.015)* |
| **Active population** | -87.84 | -152.33 | -34.97 | -95.81 | -114.28 |
| | *(0.005)* | *(0.001)* | *(0.385)* | *(0.003)* | *(0.032)* |
| **Education** | 17.60 | 6.33 | 17.77 | 18.35 | 8.31 |
| | *(0.007)* | *(0.467)* | *(0.008)* | *(0.005)* | *(0.488)* |
| **Unknown** | 2.03 | 4.05 | 1.78 | 2.41 | 2.12 |
| | *(0.012)* | *(0.001)* | *(0.010)* | *(0.004)* | *(0.031)* |
| **Arrested** | -0.03 | -0.06 | -0.04 | -0.04 | -0.05 |
| | *(0.083)* | *(0.007)* | *(0.068)* | *(0.015)* | *(0.002)* |
| Population density | 8.52 | 8.19 | 7.81 | 8.37 | 4.40 |
| | *(0.107)* | *(0.128)* | *(0.106)* | *(0.119)* | *(0.504)* |
| Trade | | 5.28 | | | |
| | | *(0.016)* | | | |
| Public spending | | | 111.66 | | |
| | | | *(0.007)* | | |
| Financial Development | | | | -93.58 | |
| | | | | *(0.091)* | |
| Sex Ratio | | | | | 93.26 |
| | | | | | *(0.156)* |
| Regions/Obs | 19/380 | 19/380 | 19/380 | 19/380 | 19/380 |
| Number of instruments | 25 | 25 | 25 | 25 | 25 |
| Hansen *J*-test (*p*-value) | 0.752 | 0.926 | 0.625 | 0.835 | 0.704 |
| AR(1) test (*p*-value) | 0.053 | 0.023 | 0.025 | 0.026 | 0.034 |
| AR(2) test (*p*-value) | 0.446 | 0.499 | 0.599 | 0.362 | 0.755 |
| No. of lags of endogenous variables used as instruments | (2 4) | (2 4) | (2 4) | (2 4) | (2 4) |

*Notes*: Dependent variable is OC Index 5. *p*-values in parentheses. Constant term not reported. All regressions based on system-GMM. Instrumented control variables are in bold type.

**Table 5**
**Robustness of Benchmark Findings for Crime**
**(Additional Control Variables)**

| | [1] | [2] | [3] | [4] | [5] |
|---|---|---|---|---|---|
| **Log GDP per capita** | 2.24 | 2.66 | 6.31 | 10.05 | -1.33 |
| | *(0.490)* | *(0.421)* | *(0.114)* | *(0.016)* | *(0.735)* |
| **GDP pc growth** | -10.58 | -7.03 | 3.20 | -19.63 | -1.39 |
| | *(0.048)* | *(0.331)* | *(0.637)* | *(0.005)* | *(0.862)* |
| **Active population** | -16.61 | -15.91 | -8.09 | -51.09 | -4.60 |
| | *(0.235)* | *(0.279)* | *(0.647)* | *(0.001)* | *(0.746)* |
| **Education** | 0.28 | 0.14 | -0.43 | 1.15 | 3.12 |
| | *(0.897)* | *(0.952)* | *(0.881)* | *(0.704)* | *(0.234)* |
| **Unknown** | 2.63 | 2.51 | 2.57 | 2.64 | 2.20 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.058)* | *(0.021)* |
| **Arrested** | -1.21 | -1.21 | -0.90 | -1.83 | -1.28 |
| | *(0.032)* | *(0.038)* | *(0.100)* | *(0.009)* | *(0.050)* |
| Population density | 0.53 | 0.04 | 0.72 | 2.78 | 0.73 |
| | *(0.675)* | *(0.981)* | *(0.569)* | *(0.013)* | *(0.436)* |
| Trade | | -0.14 | | | |
| | | *(0.787)* | | | |
| Public spending | | | 61.76 | | |
| | | | *(0.006)* | | |
| Financial Development | | | | -74.22 | |
| | | | | *(0.000)* | |
| Sex Ratio | | | | | 22.04 |
| | | | | | *(0.425)* |
| Regions/Obs | 19/380 | 19/380 | 19/380 | 19/380 | 19/380 |
| Number of instruments | 25 | 25 | 25 | 25 | 25 |
| Hansen *J*-test (*p*-value) | 0.981 | 0.977 | 0.995 | 0.789 | 0.938 |
| AR(1) test (*p*-value) | 0.045 | 0.069 | 0.072 | 0.038 | 0.068 |
| AR(2) test (*p*-value) | 0.621 | 0.644 | 0.623 | 0.571 | 0.695 |
| No. of lags of endogenous variables used as instruments | (2 4) | (2 4) | (2 4) | (2 4) | (2 4) |

*Notes*: Dependent variable is rate of intentional homicides. *p*-values in parentheses. Constant term not reported. All regressions based on system-GMM. Instrumented control variables are in bold type.

**Table 6**
**Robustness of Benchmark Findings for Organized Crime**
**(Alternative Measures of Organized Crime)**

| | **OC Index5** | **OC Index5 + Kidnapping for extortion** | **OC Index5 + Kidnapping for extortion+Arsons** | **OC Index CRENOS** |
|---|---|---|---|---|
| | **[1]** | **[2]** | **[3]** | **[4]** |
| **Log GDP per capita** | 1.54 | -4.18 | 51.54 | 9.45 |
| | *(0.848)* | *(0.596)* | *(0.000)* | *(0.001)* |
| **GDP pc growth** | 19.73 | 16.81 | 63.62 | -11.38 |
| | *(0.018)* | *(0.101)* | *(0.108)* | *(0.207)* |
| **Active population** | -87.84 | -73.99 | -264.21 | -74.23 |
| | *(0.005)* | *(0.045)* | *(0.000)* | *(0.000)* |
| **Education** | 17.60 | 22.83 | 24.79 | 3.28 |
| | *(0.007)* | *(0.000)* | *(0.042)* | *(0.248)* |
| **Unknown** | 2.03 | 2.88 | 6.88 | 1.01 |
| | *(0.012)* | *(0.001)* | *(0.000)* | *(0.005)* |
| **Arrested** | -0.03 | -0.06 | -0.17 | -1.94 |
| | *(0.083)* | *(0.002)* | *(0.025)* | *(0.002)* |
| Population density | 8.52 | 12.53 | 12.15 | 6.92 |
| | *(0.107)* | *(0.015)* | *(0.005)* | *(0.000)* |
| Regions/Obs | 19/380 | 19/380 | 19/380 | 19/304 |
| Number of instruments | 25 | 25 | 25 | 25 |
| Hansen *J*-test (*p*-value) | 0.756 | 0.836 | 0.681 | 0.621 |
| AR(1) test (*p*-value) | 0.053 | 0.030 | 0.110 | 0.098 |
| AR(2) test (*p*-value) | 0.446 | 0.611 | 0.224 | 0.017 |
| No. of lags of endogenous variables used as instruments | (2 4) | (2 4) | (2 4) | (2 4) |

*Notes*: Dependent variable is a measure of organized crime. *p*-values in parentheses. Constant term not reported. All regressions based on system-GMM. Instrumented control variables are in bold type.

**Table 7**
**Robustness of Benchmark Findings for Crime**
**(Alternative categories of crime)**

| | **Homicides** [1] | **Thefts** [2] | **Robberies** [3] | **Fraud** [4] |
|---|---|---|---|---|
| **Log GDP per capita** | 2.24 | 5.38 | 16.86 | -0.81 |
| | *(0.490)* | *(0.000)* | *(0.006)* | *(0.000)* |
| **GDP pc growth** | -10.58 | 2.22 | -11.96 | -0.29 |
| | *(0.048)* | *(0.184)* | *(0.255)* | *(0.077)* |
| **Active population** | -16.61 | -10.55 | -67.10 | 3.04 |
| | *(0.235)* | *(0.009)* | *(0.000)* | *(0.000)* |
| **Education** | 0.28 | -2.29 | -6.24 | 0.41 |
| | *(0.897)* | *(0.004)* | *(0.140)* | *(0.003)* |
| **Unknown** | 2.6326 | -2.58 | 1.06 | 0.54 |
| | *(0.000)* | *(0.868)* | *(0.007)* | *(0.000)* |
| **Arrested** | -1.21 | -2.4 | -0.08 | 0.03 |
| | *(0.032)* | *(0.815)* | *(0.805)* | *(0.000)* |
| Population density | 0.53 | -0.11 | -0.39 | 0.02 |
| | *(0.675)* | *(0.677)* | *(0.765)* | *(0.510)* |
| Regions/Obs | 19/380 | 19/380 | 19/380 | 19/380 |
| Number of instruments | 25 | 25 | 25 | 25 |
| Hansen *J*-test (*p*-value) | 0.981 | 0.641 | 0.851 | 0.765 |
| AR(1) test (*p*-value) | 0.045 | 0.047 | 0.116 | 0.002 |
| AR(2) test (*p*-value) | 0.621 | 0.002 | 0.562 | 0.108 |
| No. of lags of endogenous variables used as instruments | (2 4) | (2 4) | (2 4) | (2 4) |

*Notes*: Dependent variable is a different category of crime. *p*-values in parentheses. Constant term not reported. All regressions based on system-GMM. Instrumented control variables are in bold type.