Crime and regional growth in Italy

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Abstract

Building on standard growth-theory models, this paper provides an empirical investigation of the effects of crime on regional economic performance in Italy, as measured by labour productivity growth. Our analysis relies on a panel of annual data on the Italian regions and, contrary to previous studies in the field, adopts a flexible and efficient panel estimation approach which controls for parameter heterogeneity, cross-section dependence and variable endogeneity via mean-group estimation, multifactor modelling and Granger-causality methods. Our results strongly support the hypothesis that crime has significant negative effects on regional growth in Italy.

Keywords: Crime, regional growth, panel data, multifactor modeling.

JEL Classifications: C23, O40, R10.

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1. Introduction

Despite the intense process of development and structural change undergone since the 1950s, which has turned Italy into one of the world's most advanced economies, regional development gaps are still a typical feature of the Italian economy. The economic divide is particularly significant between the affluent Northern regions and the eight Southern regions belonging to the so called *Mezzogiorno* – Abruzzo, Basilicata, Calabria, Campania, Molise, Apulia, Sicily and Sardinia – and has proved remarkably persistent to economic policy intervention, independently of the criteria used to measure it. As such, Italian regional disparities have attracted much attention in the literature (e.g. Lanzafame, 2009, 2010; Maffezzoli, 2006; Paci and Pigliaru, 1997).

One of the less-studied aspects of this phenomenon relates to the role played by crime, and particularly violent criminal activity, in hampering Italian regions' growth and development. Reflecting a general trend in the economics of crime literature, most empirical research in the field focuses on the economic and social determinants of crime in Italy, rather than on its economic effects (e.g. Buonanno and Leonida, 2009; Bianchi et al., 2012). This is somewhat puzzling, given the substantial evidence on the social and financial costs associated to criminal activities (e.g. Czabanski, 2008), and is even more surprising in the case of Italy, where the incidence of violent crime is particularly high in some of the poor Southern regions, historically characterised by a deep-rooted presence of organised, *mafia*-type criminal organisations.

From a theoretical viewpoint, there are several reasons to expect crime to have a considerable impact on economic performance and, especially, productivity growth via various (direct and indirect) channels. Criminal activities are likely to influence negatively physical capital accumulation, by increasing the risk of entrepreneurship and effectively imposing a tax on the returns to investment, as some resources need to be used to protect businesses from (and/or insure

them against) possible theft, destruction of property, extortion and other crime-related damages. This can lead to lower levels of both domestic and foreign private investment. Similarly, the more significant the incidence of law-breaking behaviour, the larger the share of public resources which will be devoted to security purposes, thus crowding out public expenditure on productive assets (e.g. infrastructure, education) and reducing public capital accumulation. High crime levels are also detrimental to the development of good business environments and, by damaging social relations and eroding confidence in public institutions and the rule of law, they can disrupt local learning interactions and knowledge spillovers between firms, thus reducing positive externalities such as those characterising many thriving industrial districts in the North-Eastern and Central regions of Italy. Furthermore, crime can decrease the incentive for human capital accumulation, insofar as a high-crime environment raises expected returns to criminal activities *vis-à-vis* returns to legal productive work. All of these detrimental effects are amplified in areas heavily characterised by the presence of organised crime, which typically profits from distorting market competition via corruption, intimidation and violence, thus leading to suboptimal economic outcomes.

A number of recent studies have investigated empirically the effects of crime on economic growth in Italy. Among these, Detotto and Otranto (2010) use monthly data from January 1979 to September 2002 and a state-space model to examine the economic effects of crime on aggregate (national) GDP in Italy. Their results indicate that crime, as proxied by the murder rate, is linked to economic growth by a significantly negative relationship, which appears to be characterised by cyclical components. Peri (2004) uses provincial data over the 1951-1991 years to investigate the influence of socio-cultural factors on economic performance in Italy, focusing on (private sector) employment and per-capita GDP. His analysis is based on cross-section estimations and provides only weak evidence that 'social capital' (Putnam, 1993) fosters economic success. On the contrary, the results strongly indicate that provincial murder rates at the beginning of the period, which Peri (2004) interprets as an index for the presence of organised crime, are associated with low subsequent economic development. Mauro and Carmeci (2007) develop an overlapping generation

exogenous growth model, as well as an endogenous growth version of it, to analyse the interactions between crime, growth and unemployment. They assess the empirical performance of the model using annual data on the Italian regions over the 1963-1995 period and the Pooled Mean Group (PMG) panel estimator proposed by Pesaran et al. (1999). The PMG results favour the exogenous variant of the model and indicate that crime, proxied by the regional homicide rate, has significantly negative long-run effects on the level of per-capita GDP, but not on its growth rate. Daniele and Marani (2011) focus on the effects of crime on foreign direct investment (FDI), using a panel of 103 Italian provinces over the 2002-2006 years. To deal with group-wise heteroskedasticity, they base their econometric analysis on group-wise weighted least square (WLS) estimation, a particular type of Feasible Generalised Least Square (FGLS) estimation for panel data. The WLS estimator provides robust evidence of a negative correlation between an index of the presence of organised crime and FDI, even after controlling for a number of typical FDI determinants. As in Peri (2004), Pinotti (2012) uses regional murder rates as a proxy for the presence of organised crime and assesses the economic influence of the latter by focusing on the two Southern regions of Apulia and Basilicata which, from the early 1970s, experienced a significant increase in mafia-type activities. Comparing their economic performance over a thirty-year period, Pinotti (2012) finds that Apulia's and Basilicata's growth trajectories were significantly damaged by the appearance of organised crime which, starting from the mid-1970s, led to a fall of about 16 percent in per-capita GDP with respect to a control group of other Italian regions less significantly exposed to mafia-type organisations.

Following this recent line of research, this paper investigates the effects of crime on regional economic performance in Italy, as measured by labour productivity growth. Rather than relying on *a priori* assumptions about the potential determinants of the relationship between growth and crime and the various channels via which they might operate, we adopt a reduced-form approach, grounded in standard growth theory and aimed at examining aggregated outcomes directly.

Our empirical analysis makes a number of contributions to the literature. We rely on a panel of annual data on the Italian regions but, contrary to previous panel studies which are typically based on standard estimators, we adopt a more flexible and efficient panel estimation framework which controls for a number of issues usually affecting panel methods. Among these, parameter heterogeneity and cross-section dependence among the panel groups are of particular importance. Standard panel techniques (e.g. the pooled or fixed-effects estimators) impose a high degree of parameter homogeneity but, as a result of different economic structures, social capital endowments and other characteristics, not least the strength of organised crime, the effects of criminal activities are likely to be heterogeneous across Italian regions. In such a case, standard panel estimators are thus fundamentally misspecified and will yield biased results (Pesaran and Smith, 1995). Meanwhile, cross-section dependence can arise in panels from the presence of common factors. Italian regions interact via economic, trade, political and other channels and, being part of the same national entity, are affected by common phenomena ranging from national policy changes to country-wide economic shocks such as the recent financial and sovereign debt crises. This is likely to result in cross-section correlation in the cross-region panel, which leads to biased estimates and incorrect inference in standard panel estimators based on the assumption of cross-section independence (Pesaran, 2006). Our empirical strategy deals with these issues relying on mean-group estimation and multifactor modelling methodologies. Specifically, we make use of the traditional mean-group (MG) estimator (Pesaran and Smith, 1995), as well as two recently-developed multifactor modelling approaches – the 'Common Correlated Effects Mean Group' (CCEMG) estimator put forward by Pesaran (2006) and the 'Augmented Mean Group' (AMG) technique developed by Eberhardt and Teal (2012b). The MG approach allows for parameter heterogeneity and region-specific elements while, in addition, the CCEMG and AMG estimators also account for cross-section dependence arising from common factors.

A further issue typically associated to empirical growth studies is the concern over variable endogeneity. The multifactor framework at the basis of CCEMG and AMG estimation can

accommodate endogeneity when this arises from common factors driving both the dependent and independent variables. Following Eberhardt and Teal (2012a), we also deal with a more fundamental type of endogeneity determined by 'reverse causality', relying on (panel) Granger-causality methods.

The remainder of the paper is organised as follows. Section 2 provides a brief description and a preliminary analysis of the data, while Section 3 presents the empirical methodology and a first set of results based on a simple growth model. The main results of the paper, centred on a more complete model, panel multifactor modelling as well as Granger causality methods, are detailed and discussed in Section 4. Section 5 dwells on the implications of the results obtained in this paper, while Section 6 concludes.

2. Data and preliminary analysis

To investigate the impact of crime on regional growth in Italy we rely on a (slightly unbalanced) panel dataset of annual data on the Italian regions over the 1970-2005 period.[1] We focus on real GDP per unit of labour and, adopting a well-established practice in the literature, measure regional criminal activity using data on (attempted and committed) intentional homicide rates.[2] These are commonly deemed to provide a good proxy for the incidence of criminal activity, since they are usually highly correlated with other crime rates and, more importantly, contrary to other types of crime they are not plagued by underreporting, which is at most trivial in the case of intentional homicides (e.g. Detotto and Otranto, 2010; Mauro and Carmeci, 2007).[3] Data are taken from

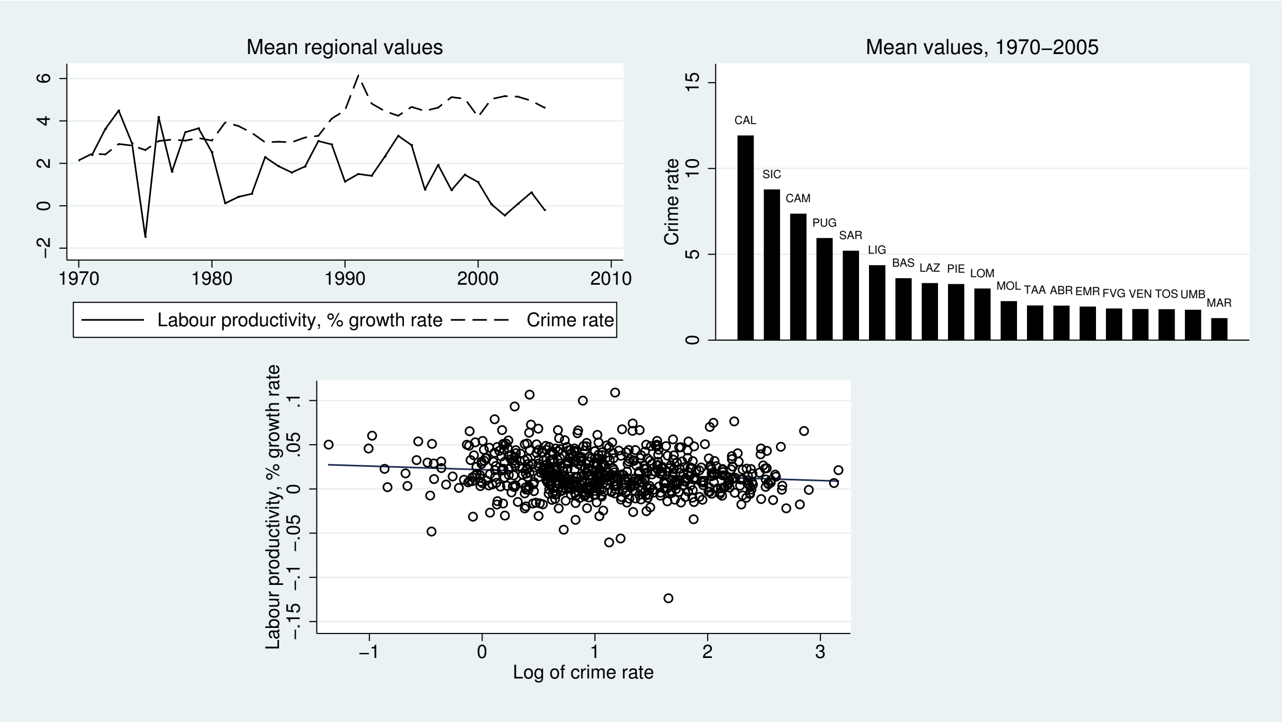
[1] The time-period under analysis is determined by data availability. In empirical studies on the 20 Italian regions, the small region Valle d'Aosta is often either excluded from the analysis altogether or embodied into the Piedmont region (e.g. Mauro and Carmeci, 2007): We follow the latter practice. For a complete list of the Italian regions and the regional codes used in this paper, see Table A1 in the Appendix.

[2] For simplicity, in the remaining part of the paper we will refer to these as 'homicide rates' or 'crime rates'.

[3] As mentioned, both Peri (2004) and Pinotti (2012) consider the murder rate as a proxy for the presence of organised crime, but this interpretation may be problematic. Frequent violent criminal acts and, especially, homicides are

regional databases constructed by the 'Centre for North South Economic Research' (CRENoS) and the Italian National Institute of Statistics (ISTAT).[4] In particular, intentional homicide statistics are based on data published by ISTAT as '*Le Statistiche della Criminalità*' (i.e. 'Crime Statistics') and collected by the judicial system when penal prosecution, which in Italy is mandatory, starts.[5]

Figure 1. Descriptive statistics



undoubtedly typically associated to organised crime in the Southern regions of Italy, but much recent evidence from police investigations, criminal trials and/or other sources (e.g. confidential surveys, the Italian Parliamentary Anti-Mafia Commission) indicates that mafia-type criminal organisations have developed pervasive ramifications in the Northern regions as well, acquiring strong economic interests and operating via more subtle and less violent methods (e.g. Calderoni, 2011). Thus, a lower average regional murder rate cannot be taken as a definite sign of the absence (or lesser influence) of organised crime, especially because it may in fact characterise the regions where the economic impact of organised crime is more significant.

[4] CRENoS is a research centre set up jointly by the University of Cagliari and the University of Sassari. The CRENoS regional databases are available online at http://crenos.unica.it/crenos/en.

[5] Official crime statistics in Italy can also be recovered from records of people's complaints collected by police corps and published by ISTAT as '*Le Statistiche della Delittuosità*'. The two datasets differ whenever the initial judge decides that the complaint does not constitute a crime, the judicial activity is delayed with respect to the time that the crime was committed or a crime is reported to public officials who do not belong to the police corps.

Figure 1 illustrates some features of the data. The top-left panel of the figure shows the evolution of the mean regional values for labour productivity growth, measured by real GDP per unit of labour, and the crime rate. While the latter displays a rather pronounced upward trend, growing from 2.14 (committed or attempted) intentional homicides per 100,000 people in 1970 to 4.62 in 2005, labour productivity growth is characterised by a negative trend, particularly pronounced from the mid-1990s onwards. The top-right graph shows that there is a remarkable variability in regional crime rates in Italy, the mean values in the period ranging from about 1.27 in the case of Marche (MAR) to 11.91 for Calabria (CAL). It can also be noted that six out of the seven highest average homicide rates are associated to *Mezzogiorno* regions, the exception being the North-Western region of Liguria (LIG).

Finally, the bottom panel of Figure 1 displays a scatter plot of regional labour productivity growth and the log of the crime rate, revealing a negative correlation between the two. The main objective of this paper is to investigate the nature and significance of this relationship.

3. Model and empirical methodology

The arguments put forward in the literature and laid out in the introduction suggest that criminal activity can damage economic performance via its (direct and indirect) impact on total factor productivity (TFP) and labour productivity growth. To investigate this hypothesis, we start by considering the following simple panel growth model with crime effects

$$Y_{it} = A_{it} L_{it} \tag{1}$$

$$\frac{\Delta A_{it}}{A_{it}} = \omega_i + \lambda_i CR_{it} \tag{2}$$

where $i = 1, 2, ..., N$ indicates the cross-sections (groups) and $t = 1, 2, ..., T$ the time periods, Y_{it} is real aggregate output, L_{it} measures labour units and CR_{it} is an index of crime incidence, defined by the number of (attempted and committed) intentional homicides per 100,000 people. The term A_{it} defines TFP and, since labour is the only production factor in (1), it also indicates the level of labour productivity. Equation (2) reflects the hypothesis that the evolution of A_{it} depends on exogenous labour productivity growth (ω_i) and crime. From (1) and (2) we obtain the dynamic labour-intensive growth equation

$$p_{it} = \omega_i + \lambda_i CR_{it} \tag{3}$$

where p_{it} defines the growth rate of output per unit of labour. For estimation purposes, we allow for a more general lag structure and rely on the following Autoregressive Distributed Lag (ARDL) transformation of the model in (3)

$$p_{it} = \omega_i + \sum_{q=0}^{Q} \rho_{iq} p_{i,t-q} + \sum_{j=0}^{J} \lambda_{ij}^{'} CR_{it-j} + u_{it} \tag{4}$$

where the optimal lag order is chosen via appropriate selection criteria.

3.1. Estimation framework

Our estimation methodology builds on a common-factor framework which, following Eberhardt and Teal (2012a, 2012b), can be formalised as follows. To simplify notation, consider a static version of (4) and, for $i = 1, 2, ..., N$, $t = 1, 2, ..., T$, let

$$p_{it} = \omega_i + \lambda_i' CR_{it} + u_{it} \qquad u_{it} = \phi_i' f_t + \varepsilon_{it} \tag{5}$$

$$CR_{it} = \pi_i + \varphi_i' g_t + \vartheta_{1i} f_{1t} + \ldots \vartheta_{ni} f_{nt} + \upsilon_{it} \tag{6}$$

$$f_t = o' f_{t-1} + \varsigma_t \qquad \text{and} \qquad g_t = \kappa' g_{t-1} + \varsigma_t \tag{7}$$

where $f_{\cdot t} \subset f_t$. In this setup, cross-section dependence is captured by a set of unobservable common factors f_t, with region-specific factor loadings ϕ_i. The error component ε_{it} is assumed to be independently distributed with zero mean and variance σ^2.

The empirical representation of CR_{it} as driven by sets of common factors g_t and f_{nt} allows for its possible endogeneity, as f_{nt} may represent a subset of the common factors driving p_{it}. The factors g_t and f_t can be persistent over time or even nonstationary ($o = 1$, $\kappa = 1$), which allows for potential nonstationarity in CR_{it} and various combinations of cointegration between p_{it} and CR_{it} or between p_{it}, CR_{it} and the common factors f_t, as well as noncointegration. Note that, while the model in (5)-(7) includes only one (observable) regressor $\left(CR_{it}\right)$, its properties apply to the multiple-covariate case too.

Provided that both N and T are sufficiently large, estimation of panel models can be performed with several alternative approaches, allowing for various degrees of parameter heterogeneity. On one extreme, the pooled estimator imposes full-homogeneity of slope and intercept coefficients, while the fixed-effects estimator allows only the intercepts to differ across groups. If the coefficients are in fact heterogeneous, these estimators will produce inconsistent and misleading results. At the other extreme, the fully heterogeneous-coefficient model is fitted separately for each group, imposing no cross-group parameter restrictions. The mean of the parameters across groups can be estimated consistently by the simple arithmetic average of the coefficients – this is the Mean Group (MG) estimator introduced by Pesaran and Smith (1995).

Though accounting for parameter heterogeneity, as other standard panel estimators the MG approach is based on the hypothesis of cross-section independence, and thus assumes away $\phi_i' f_t$ or, at best, models these unobservable factors with a linear trend. As mentioned, this leads to inconsistent and biased estimates when cross-section dependence is in fact present in the data. To correct for this drawback, Pesaran (2006) develops an estimation procedure named 'Common Correlated Effects' (CCE) estimation, which provides consistent estimates in panel data models with a general multifactor error structure. The basic intuition that CCE estimation builds upon is that the unobservable common factors f_t can be proxied via cross-sectional averages of the observable variables. Following Pesaran (2006), under the assumption that slope coefficients and regressors are uncorrelated, substituting for u_{it} and averaging (5) across *i* we have

$$f_t = \bar{\phi}^{-1}\left(\bar{p}_t - \bar{\omega} - \bar{\lambda}'\overline{CR}_t - \bar{\varepsilon}_t\right) \qquad (8)$$

where $\bar{\phi} = N^{-1}\sum_{i=1}^{N}\phi_i$; $\bar{p}_t = N^{-1}\sum_{i=1}^{N} p_{it}$; $\bar{\omega} = N^{-1}\sum_{i=1}^{N}\omega_i$; $\bar{\lambda} = N^{-1}\sum_{i=1}^{N}\lambda_i$, $\overline{CR}_t = N^{-1}\sum_{i=1}^{N} CR_{it}$ and $\bar{\varepsilon}_t = N^{-1}\sum_{i=1}^{N}\varepsilon_{it}$. For $N \to \infty$ and $\bar{\phi} \neq 0$, $\bar{\varepsilon}_t = 0$ and cross-sectional correlation can be controlled for via a linear combination of the cross-sectional averages of dependent and independent variables. Modifying the model in (5) accordingly we have

$$p_{it} = \omega_i + \lambda_i' CR_{it} + d_{1i}\bar{p}_t + d_{2i}\overline{CR}_t + \varepsilon_{it} \qquad (9)$$

The Common Correlated Effects Mean Group (CCEMG) estimator results from MG estimation of (9). The CCEMG approach produces consistent estimates of the model parameters as simple

averages of the group-specific estimates, e.g. $\hat{\lambda}_{CCEMG} = N^{-1}\sum_{i=1}^{N}\hat{\lambda}_i$.[6] Notice that CCE estimation does not produce explicit estimates for the unobserved factors f_t or factor loadings ϕ_i. The estimated coefficients on the cross-section averaged variables in the CCE setup have no meaningful economic interpretation, being included solely to purge the bias arising from the presence of unobservable common factors. Moreover, standard CCE estimation does not include a deterministic trend, as this is simply a type of common factor. Nonetheless, the model in (9) can be augmented with a linear trend term, to capture omitted idiosyncratic processes evolving in a linear fashion over time.

Eberhardt and Teal (2012b) have recently proposed an alternative approach, termed Augmented Mean Group (AMG) estimation, which accounts for cross-section dependence by including a 'common dynamic process' in the group regressions. The AMG estimator is based on the following two-stage procedure:

$$\Delta p_{it} = \lambda' \Delta CR_{it} + \sum_{t=2}^{T} c_t \Delta D_t + e_{it} \qquad \Rightarrow \hat{c}_t \equiv \hat{\mu}_t^{\bullet} \tag{10}$$

$$p_{it} = \omega_i + \lambda_i' CR_{it} + c_i t + d_i \hat{\mu}_t^{\bullet} + e_{it} \tag{11}$$

The first stage is carried out via pooled OLS regression of the first-differences model in (10), which is augmented with the $T-1$ year dummies D_t. The coefficients on the (differenced) year dummies, relabelled as $\hat{\mu}_t^{\bullet}$, represent an estimated cross-group average of the evolution of unobservables over time, referred to as the 'common dynamic process'.[7] Intuitively, if f_t is truly common across groups, in each year t the coefficient on the year dummy variable D_t in (10) provides an average estimate of the common factors across groups in that particular year and the inclusion of $T-1$ year dummies

[6] When the individual slope coefficients are homogenous across *i*, a more efficient estimator can be obtained via pooled estimation of (9), resulting in the Common Correlated Effects Pooled (CCEP) estimator.

[7] The 'common dynamic process' is extracted from the pooled regression in *first differences* as unobservables (as well as the possible presence of nonstationary variables) would lead to biased estimates in pooled *levels* regressions.

produces an estimate (i.e. $\hat{\mu}_t^{\bullet}$) of how the common factors f_t evolve over time. In the second stage (11), the estimated process can be imposed on each group member with unit coefficient, by subtracting $\hat{\mu}_t^{\bullet}$ from the dependent variable. Alternatively, the N group-specific regressions are augmented with $\hat{\mu}_t^{\bullet}$ as an explicit variable.[8] Thus, contrary to the CCE approach, AMG estimation uses an *explicit* estimate for f_t so that the common dynamic process $\hat{\mu}_t^{\bullet}$ is an economically meaningful construct. In a cross-region growth model such as ours, $\hat{\mu}_t^{\bullet}$ can be interpreted as common labour productivity or, more generally, Total Factor Productivity (TFP) evolution over time, while d_i represents the implicit factor loading on common TFP.[9] As for the MG and CCEMG estimators, the group-specific AMG estimates are averaged across the panel so that $\hat{\lambda}_{AMG} = N^{-1}\sum_{i=1}^{N}\hat{\lambda}_i$. Each regression model in the AMG setup can also include a linear trend term to capture idiosyncratic time-varying unobservables evolving linearly over time. The Monte Carlo simulations in Bond and Eberhardt (2009) indicate that the inclusion of $\hat{\mu}_t^{\bullet}$ allows for the separate identification of λ_i and the unobserved common factors f_t and g_t, and that the small-sample performance of the AMG approach broadly matches that of the CCEMG estimator.

Both the CCEMG and AMG methods are sufficiently general to allow for potentially nonstationary and/or nonlinear observables and unobservables, as well as idiosyncratic or global business cycle effects. Thus, we can exploit all the information available in the dataset using annual-data estimation without incurring in the distorting influence normally associated to business cycle components in this type of empirical analysis.

8 Regarding the issues associated to second stage 'regressions with generated regressors' (Pagan, 1984), Eberhardt and Teal (2012b) point to the theoretical results in Bai and Ng (2008), who show that second stage standard errors need not be adjusted for first stage estimation uncertainty if $\sqrt{T}/N \rightarrow 0$, as is arguably the case here. This is supported by simulation results in Bond and Eberhardt (2009), indicating that the average standard error of AMG estimates is of similar magnitude to the empirical standard deviation.

9 Indeed, this is the key feature of the AMG estimator, which Eberhardt and Teal (2012b) develop as an alternative to the CCE approach for macro production function estimation.

3.2. Estimation results

We start by performing standard MG estimation of the ARDL model in (4) and, subsequently, test formally for the presence of cross-section dependence.[10] Following a common practice in the literature (e.g. Loayza and Ranciere, 2006), we impose the same lag order to all of the panel cross-sections, chosen in accordance to the model and data limitations. According to the Schwarz Bayesian Criterion (SBC), the ARDL (1,0) is the appropriate model for most of the cross-sections in our panel, so that we adopt this model throughout the econometric work in this section.[11] This choice is consistent with the use of annual data and minimizes the loss of degrees of freedom.

Since underreporting may result in biased econometric estimates, many studies in the literature make use of the crime rate in logarithmic form $(\ln CR_{it})$ as a way of reducing the impact of this type of measurement error (e.g. Bianchi et al., 2012). We follow this practice but, for completeness purposes and since underreporting does not represent a serious concern in our case, we also perform our estimations using the absolute value of the crime rate (CR_{it}). The two sets of estimations will provide us with different information on the role played by crime, as the estimated coefficient on CR_{it} will indicate the effect of an absolute change in the crime rate on labour productivity growth, while that on $\ln CR_{it}$ returns the elasticity of p_{it} with respect to the crime rate.

The MG estimation results are reported in Table 1. Standard errors and parameter estimates were constructed following the procedure proposed by Hamilton (1991), which attributes less weight to outliers in their computation. For all of the four specifications considered, we find clear supportive evidence in favour of the hypothesis that crime has significant negative effects on

[10] As a preliminary step, we assessed the stationarity properties of each regional CR_{it} series via the classic Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979). The ADF results, reported in Table A1 in the Appendix, reject the unit-root null in almost all cases, indicating that the crime rate can be modelled as a trend-stationary variable.

[11] We carried out lag selection tests for all regressions using also general-to-specific modelling methods. In all cases, the ARDL(1,0) turned out to be the most suitable model for the panel as a whole.

growth. However, the finding of 5 and 6 significant region-specific time trends in two estimations may signal the possible presence of common factors and, thus, cross-section dependence. As pointed out, in such a case standard panel methods, such as the MG estimator, break down and may yield biased results. Thus, we carry out a formal investigation of this hypothesis making use of a test of cross-section dependence (CD) developed by Pesaran (2004).

Table 1. Standard MG estimations and CD test

Estimator	MG	MG	MG	MG
Dependent variable	p_{it}	p_{it}	p_{it}	p_{it}
p_{it-1}	-0.010	-0.080^	-0.005	-0.072^
CR_{it}	-0.005**	-0.002**		
$\ln CR_{it}$			-0.015**	-0.010**
Intercept	0.032**	0.035**	0.035**	0.039**
# of region-specific trends significant at 10%		5		6
CD stastistic	25.66	25.25	26.07	25.44
p-value	0.000	0.000	0.000	0.000

Notes: ** and ^ indicate, respectively, significant at the 1% and 10% level. Parameter estimates and standard errors were computed via the outlier-robust procedure in Hamilton (1991).

The CD test statistic is based on mean pairwise correlation coefficients for variable series or regression residuals and, in the case of unbalanced panels, is defined as

$$CD = \sqrt{\left(\frac{2}{N(N-1)}\right)\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\sqrt{T_{ij}}\,\widehat{\rho}_{ij}\right)} \tag{12}$$

where $\widehat{\rho}_{ij}$ indicates the pairwise correlation coefficients between all regional series, while T_{ij} is the number of observations used to estimate the correlation coefficient between the series in regions i and j. For $T_{ij} > 3$ and sufficiently large N, under the null of cross-section independence

$CD \sim N(0,1)$. Moreover, the CD test is robust to the presence of nonstationary processes, parameter heterogeneity or structural breaks, and was shown to perform well even in small samples.

Using the residuals from the MG regressions, we performed the CD test to ascertain the presence of cross-section dependence for all regressions in Table 1. As can be seen from the bottom rows in the table, the null of cross-section independence is strongly rejected in all cases. As mentioned, this outcome implies that standard MG estimation is likely to produce misleading inference since an appropriate estimation strategy should control for cross-section dependence. Thus, we now proceed to the implementation of CCEMG and AMG estimation methods.

Table 2. CCEMG and AMG estimations: Model specifications with CR_{it}

Estimator	CCEMG	CCEMG	AMG	AMG	AMG	AMG
Dependent variable	p_{it}	p_{it}	p_{it}	p_{it}	$p_{it} - \hat{\mu}_t^{\bullet}$	$p_{it} - \hat{\mu}_t^{\bullet}$
p_{it-1}	-0.126*	-0.140*	-0.296**	-0.307**	-0.333**	-0.325**
CR_{it}	-0.002*	-0.003**	-0.001	-0.002^	-0.001	-0.002^
Common trend			0.883**	0.892**		
Intercept	0.002	0.005	0.045**	0.046**	0.047**	0.048**
# of region-specific trends significant at 10%		3		3		3

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level. Parameter estimates and standard errors were computed via the outlier-robust procedure in Hamilton (1991).

Table 3. CCEMG and AMG estimations: Model specifications with $\ln CR_{it}$

Estimator	CCEMG	CCEMG	AMG	AMG	AMG	AMG
Dependent variable	p_{it}	p_{it}	p_{it}	p_{it}	$p_{it} - \hat{\mu}_t^{\bullet}$	$p_{it} - \hat{\mu}_t^{\bullet}$
p_{it-1}	-0.114^	-0.121*	-0.288**	-0.292**	-0.325**	-0.315**
$\ln CR_{it}$	-0.009**	-0.010**	-0.006*	-0.009**	-0.004	-0.010**
Common trend			0.883	0.888**		
Intercept	0.002	0.005	0.006^	0.008	0.002	0.007^
# of region-specific trends significant at 10%		2		3		2

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level. Parameter estimates and standard errors were computed via the outlier-robust procedure in Hamilton (1991).

Table 2 reports the results from CCEMG and AMG estimation of the models with CR_{it}. The CCEMG results confirm the supportive evidence for the hypothesis that crime has significant negative effects on labour productivity growth while, though entering with the expected negative sign, the AMG estimates of CR_{it} turn out to be significant (at 10 percent) only in two of the four AMG models considered. The estimations including the crime rate in logarithmic form, reported in Table 3, provide more consistent results. In particular, the coefficient on $\ln CR_{it}$ is always negative and turns out to be significant in five out of the six specifications.

Overall, the results indicate that each unit increase in CR_{it} leads to a fall of about 0.002 percent in labour productivity growth, while the estimated elasticity on $\ln CR_{it}$ implies a decrease of about 0.010 percent in p_{it} for a 1 percent rise in the crime rate. Before turning to a discussion of the implications of these results, in the next section we assess their robustness.

4. Extensions and robustness of the results

The simple model adopted in the previous section is centred exclusively on the relationship between labour productivity growth and the crime rate. In such a framework, any indirect effects of crime on p_{it}, working via its impact on physical and human capital accumulation, will be captured by the coefficient on CR_{it} or $\ln CR_{it}$. However, by not considering explicitly the direct effects of physical and human capital on productivity growth, the model formalised in (4) may be misspecified.

Several alternative model specifications can be relied upon to deal with this drawback (e.g. Benhabib and Spiegel, 1994; Bosworth and Collins, 2003). Following Mankiw et al. (1992), a suitable growth model can be formalised as follows:

$$Y_{it} = K_{it}^{\alpha_i} H_{it}^{\delta_i} \left(A_{it} L_{it} \right)^{1-\alpha_i-\delta_i} \tag{13}$$

where, as usual, $i=1,2,...,N$, $t=1,2,...,T$, Y_{it} is real output, L_{it} measures labour units, and A_{it} defines the level of TFP. In addition, K and H indicate, respectively, the stocks of physical and human capital and the model allows for heterogeneous output elasticities α_i and δ_i across regions. Assuming that the evolution of TFP can be described by equation (2), i.e. $\Delta A_{it}/A_{it}=\omega_i+\lambda_i CR_{it}$, the associated labour-intensive growth equation is

$$p_{it}=\gamma_i+\zeta_i CR_{it}+\alpha_i k_{it}+\delta_i h_{it} \tag{14}$$

where $\gamma_i=\omega_i\left(1-\alpha_i-\delta_i\right)$, $\zeta_i=\lambda_i\left(1-\alpha_i-\delta_i\right)$, k_{it} and h_{it} are, respectively, the growth rates of physical and human capital per unit of labour while, as before, p_{it} is the growth rate of output per unit of labour and CR_{it} is the crime rate. With respect to (4), the model in (14) provides a more complete framework in which to assess the effects of crime on regional growth in Italy. However, before proceeding to its estimation we need to address two types of issues.

The first issue relates to data availability for the regional capital stock and human capital series. Data on the stock of physical capital are not readily available for the Italian regions, so that we resort to constructing the K_{it} series using the standard perpetual inventory model (e.g. Bosworth and Collins, 2003; Caselli, 2005):

$$K_{it}=I_{it}+\left(1-d\right)K_{it-1} \tag{15}$$

where I is gross fixed investment and, following the literature, the depreciation rate d is set to 0.06.[12] As for human capital, we rely on an updated version of the dataset constructed by Tornatore et al. (2004) and compute the h_{it} series starting from the following macro-Mincer equation:

$$HL_{it} = e^{\pi(s_{it})} \tag{16}$$

where HL is human capital per unit of labour, s is the average number of years of schooling per employee and the average annual return to education is assumed to be 7 percent, i.e. $\pi = 0.07$.[13,14]

The second issue is related to the treatment of variable endogeneity. As mentioned, the multifactor approach based on CCEMG and AMG estimation takes account of one type of endogeneity, i.e. that induced by the presence of common factors. However, this may not be entirely adequate in the case of more typical endogeneity issues related to reverse causality, which in the case of the model in (14) could be running from productivity growth to physical and/or human capital accumulation, as well as crime. In line with Eberhardt and Teal (2012a), in the next section we deal with this question by means of Granger causality methods.

4.1. Panel Granger causality tests

Following Granger (1969), a stationary time series Y_t is said to 'Granger-cause' another stationary time series X_t if past values of Y_t significantly reduce the predictive error variance of X_t.

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[12] Following Caselli (2005), the initial capital stock K_{i0} is constructed as $I_{i0}/(g+d)$, where I_{i0} is the value of the investment series in the first year it is available and g is the average geometric growth rate for the investment series over the sample period considered.

[13] We are grateful to Sergio Destefanis for providing us with the updated dataset constructed by Tornatore et al. (2004).

[14] As pointed out by Bosworth and Collins (2003) and Caselli (2005), international evidence suggests that returns to education average about 7 percent in OECD countries (e.g. Bils and Klenow, 2000).

Formally, such a Granger-causality test is usually performed via a regression of X_t on its own lags and lags of Y_t, so that the hypothesis that Y_t Granger-causes X_t cannot be rejected if the lags of Y_t are found to be jointly statistically significant.

Granger-causality methods have been variously adapted to and implemented in a panel context, mostly in relation to the determinants of economic growth and both in the case of stationary and, within a cointegration approach, nonstationary variables (e.g. Attanasio *et al*., 2000; Nair-Reichert and Weinhold, 2001; Kónya, 2006). As all the variables under analysis in this paper are stationary, the use of cointegration methods is not feasible in our case.[15] Thus, we rely on a heterogeneous-parameter version of the approach put forward by Holtz-Eakin *et al*. (1988) and base our panel Granger-causality tests on the following panel vector autoregressive (VAR) model

$$X_{it} = \omega_i + \sum_{l=1}^{m} \beta_{il} X_{it-l} + \sum_{l=1}^{m} \delta_{il} Y_{it-l} + u_{it} \tag{17}$$

where, as usual, $i = 1,2,...,N$, $t = 1,2,...,T$ and ω_i represents the (group-specific) fixed effect. In keeping with the modelling methodology adopted in this paper, the specification in (17) allows for parameter heterogeneity so that the null hypothesis tested is

$$H_0 : N^{-1}\sum_{i=1}^{N} \delta_{i1} = N^{-1}\sum_{i=1}^{N} \delta_{i2} = ...N^{-1}\sum_{i=1}^{N} \delta_{il} = 0 \tag{18}$$

That is, the null hypothesis is that Y_{it} does *not* Granger-cause X_{it} (in our notation: $Y_{it} \not\rightarrow X_{it}$). To test (18) we rely on the MG estimator and, given the significant evidence of cross-section dependence

[15] As mentioned (see footnote 10), the unit-root hypothesis for regional crime rates is rejected by standard ADF tests, while stationarity can be safely assumed for the other variables in (14) – the presence of a unit root in k_{it} and/or h_{it} would imply explosive behaviour for the levels of these variables, which is completely at odds with economic theory as well as empirical evidence.

previously uncovered, we also run the panel Granger causality tests via AMG estimation, adopting the specifications which include the common dynamic process as an additional regressor.[16] Due to the limited time-series dimension of the data, we restrict the maximum number of lags and set $m = 2$. As mentioned, we are chiefly interested in ruling out the hypothesis of a causal relationship running from p_{it} to physical and/or human capital accumulation, as well as the crime rate, but for completeness purposes we run the tests for both directions of causation.

According to the results in Table 4, both the MG and AMG Granger causality tests indicate that there is no significant evidence of causation running from labour productivity growth to the crime rate or physical capital accumulation. However, the null of no causality from p_{it} to h_{it} is rejected in three out of the four models considered, so that we cannot rule out endogeneity for human capital accumulation.

Table 4. Panel Granger Causality Tests

	Estimator			
Null hypothesis	**MG**	**MG**	**AMG**	**AMG**
$p_{it} \not\rightarrow CR_{it}$	0.15	0.93	4.10	3.49
$CR_{it} \not\rightarrow p_{it}$	18.72**	9.58**	0.87	4.73^
$p_{it} \not\rightarrow k_{it}$	0.22	0.37	0.01	0.23
$k_{it} \not\rightarrow p_{it}$	8.77*	17.68**	7.05*	7.00*
$p_{it} \not\rightarrow h_{it}$	25.72**	18.57**	6.97*	4.12
$h_{it} \not\rightarrow p_{it}$	5.26^	0.53	1.66	0.38
Region-specific trends	No	Yes	No	Yes

Notes: * and ^ indicate, respectively, significant at the 5% and 10% level. '$\not\rightarrow$' indicates 'does not Granger-cause'. Standard errors were computed via the outlier-robust procedure in Hamilton (1991).

[16] We choose the AMG estimator in this case because, compared to the CCEMG alternative, it has the additional advantage of using up fewer degrees of freedom. As seen, CCE estimation requires the inclusion of cross-section averages of all the variables in the model as additional regressors: Given the large number of regressors required in a Granger-causality testing framework, this makes AMG estimation preferable to CCEMG methods.

Looking at the test results for the opposite direction of causation, we find robust support for the hypothesis that k_{it} causes p_{it} while, on the contrary, there is very little evidence that human capital accumulation Granger-causes labour productivity growth. Finally, the MG estimations provide strong indication of a causal link from CR_{it} to p_{it}, but the AMG evidence on the significance of this relationship is weaker.[17] In the next section we re-examine this issue relying on the model formalised in (14).

4.2. Extended model results

The CCEMG and AMG estimates of the model in (14) are reported in Tables 5 and 6. Based on the outcome of the Granger causality analysis, we treat k_{it} and CR_{it} (or $\ln CR_{it}$) as exogenous, while h_{it} is considered as potentially endogenous and instrumented with its own lags.[18]

The results provide very little or no evidence of significant region-specific linear trends, so that the 'no-trend' models appear to be more appropriate in this case. The latter return coefficient estimates of -0.001 on CR_{it} and -0.007 for $\ln CR_{it}$ which turn out to be always significant, as is the case for all of the twelve model specifications in Tables 5 and 6. The coefficients on physical and human capital accumulation also enter with the correct positive sign in all models, are nearly always strongly significant (particularly in the case of k_{it}) and their size is broadly in line with the typical estimates in the literature, indicating an output elasticity of about 33-38 percent for k_{it} and 11-18 percent for h_{it}.

[17] The CD test (Pesaran, 2004) indicates the presence of significant cross-section dependence in the MG estimation residuals (results not reported). This suggests that the MG estimates may not be reliable in this case.

[18] The estimation results in Tables 5 and 6 refer to models in which h_{it} is instrumented with its own first lag. We also tried out other specifications, instrumenting h_{it} with lags up to the third: The second and third lags of h_{it} were often not significant, while the results for the other variables in the model did not change.

Table 5. CCEMG and AMG extended model estimations: Specifications with CR_{it}

Estimator	CCEMG	CCEMG	AMG	AMG	AMG	AMG
Dependent variable	p_{it}	p_{it}	p_{it}	p_{it}	$p_{it} - \hat{\mu}_t^{\bullet}$	$p_{it} - \hat{\mu}_t^{\bullet}$
CR_{it}	-0.001*	-0.001*	-0.001^	-0.002^	-0.001**	-0.002*
k_{it}	0.363**	0.358**	0.378**	0.372**	0.333**	0.332**
h_{it}	0.120	0.163	0.110*	0.115*	0.121*	0.113^
Common trend			0.995**	0.992**		
Intercept	0.001	0.001	0.029**	0.029**	0.028**	0.028**
# of region-specific trends significant at 10%		0		0		1

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level. Parameter estimates and standard errors were computed via the outlier-robust procedure in Hamilton (1991). h_{it} instrumented with first lag.

Table 6. CCEMG and AMG extended model estimations: Specifications with $\ln CR_{it}$

Estimator	CCEMG	CCEMG	AMG	AMG	AMG	AMG
Dependent variable	p_{it}	p_{it}	p_{it}	p_{it}	$p_{it} - \hat{\mu}_t^{\bullet}$	$p_{it} - \hat{\mu}_t^{\bullet}$
$\ln CR_{it}$	-0.007**	-0.008**	-0.007**	-0.009**	-0.007**	-0.009**
k_{it}	0.370	0.364**	0.384**	0.376**	0.337**	0.338**
h_{it}	0.182	0.177	0.141*	0.141*	0.152*	0.137*
Common trend			0.998**	0.994**		
Intercept	0.000	0.002	0.003	0.003	0.002	0.004**
# of region-specific trends significant at 10%		1		0		0

Notes: ** and * indicate, respectively, significant at the 1% and 5% level. Parameter estimates and standard errors were computed via the outlier-robust procedure in Hamilton (1991). h_{it} instrumented with first lag.

Overall, therefore, the model formalised in (14) appears to perform well in capturing the main features of regional growth in Italy and, importantly, it reinforces the supportive evidence for the hypothesis that crime has significantly negative effects on growth.[19]

[19] We also carried out regressions of a dynamic version of (14), including p_{it-1} as an additional regressor. The results, reported in Tables A2 and A3 in the Appendix, are very similar to those Tables 5 and 6.

5. Discussion of the results

The empirical evidence gathered in this paper clearly indicates that crime has had a significant impact on the Italian regions' labour productivity performance. As most of the high-crime regions are located in the *Mezzogiorno*, this seems to suggest that the economic effects of crime may play an important role in explaining the persistence of regional disparities in Italy. One simple method to investigate this hypothesis is to use our coefficient estimates to determine the trajectories that the regional p_{it} series would have followed had the crime rate remained at some fixed level in the period under analysis. Specifically, given the high variability of crime rates across regions, it may be useful to compare the actual pattern of regional labour productivity growth to a hypothetical scenario in which, for each year over the 1970-2005 period, the crime rate of each of the 19 Italian regions is equal to the average national crime rate.

In order to do so, we focus on the model specifications with CR_{it} and construct hypothetical regional p_{it} series as $p_{it}^{*} = p_{it} - \hat{\zeta}\left(CR_{it} - \overline{CR}_i\right)$, where $\overline{CR}_i = T^{-1}\sum_{t=1}^{T} CR_{it}$ is the average annual crime rate across regions and, based on the results in Table 5, we assume $\hat{\zeta} = -0.001$. We can then calculate the implied annual productivity growth loss (*PLOSS*) as

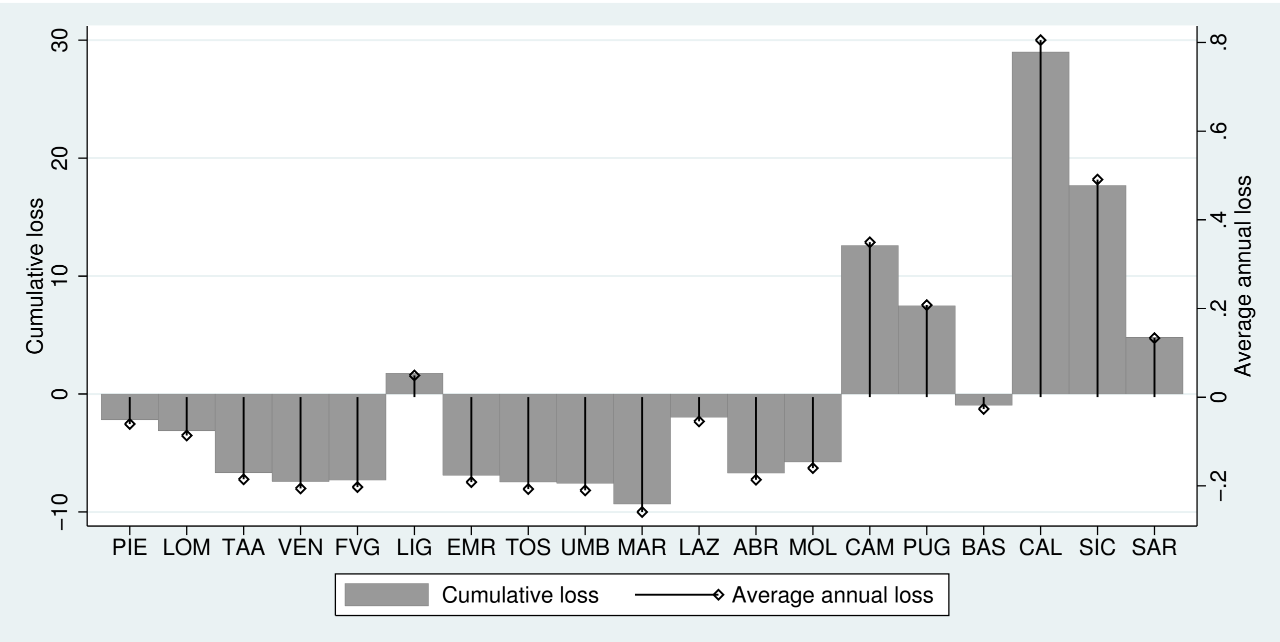
$$PLOSS_{it} = p_{it}^{*} - p_{it} = -\hat{\zeta}\left(CR_{it} - \overline{CR}_i\right) \tag{19}$$

so that $PLOSS_{it} > 0$ implies a net loss of productivity growth with respect to a scenario in which $CR_{it} = \overline{CR}_i$.

Figure 2 plots the cumulative and average annual values of *PLOSS* over the period under analysis. With the exception of Liguria, all of the Northern regions display negative values, implying a net gain in terms of labour productivity growth due to lower crime rates with respect to

the national average. The size of these gains ranges from a relatively small cumulative value of about 2.2 percent for Piedmont to about 7 – 7.50 percent in the case of Veneto, Friuli Venezia Giulia, Emilia Romagna, Tuscany and Umbria, to about 9.3 percent for Marche. On the contrary, our simulation produces positive *PLOSS* values for 5 out of the 8 *Mezzogiorno* regions. In particular, for Calabria the cumulative *PLOSS* over the 1970-2005 period is about 29 percent, which implies an annual productivity loss of about 0.8 percent due to a higher-than-average crime rate. The corresponding figures for Sicily are about 17.7 and 0.5 percent, and 12.6 and 0.35 percent in the case Campania.[20]

Figure 2. *PLOSS* by region: Models with CR_{it}, ζ = -0.001



The simulation presented in this section is subject to a number of caveats, as it is based on a hypothetical scenario in which each regional crime rate becomes equal to $\overline{CR_i}$, *all else remaining constant*. In reality, changes in CR_{it} are unlikely to take place in isolation and, as pointed out, affect other determinants of productivity growth, such as physical and human capital accumulation. Thus, the results in Figure 2 should be considered with caution and not taken at face value, but they do

[20] For the complete set of results, see Table A4 in the Appendix.

indicate that the benefits associated to the reduction of violent crime rates in the high-crime regions may be quite significant.

6. Conclusions

This paper provides an empirical investigation of the effects of crime on regional growth in Italy. From a theoretical viewpoint, there are several channels via which crime and, particular, violent criminal activities can exert a damaging influence on economic performance and, given the considerable variability in regional crime rates in Italy, we focus on assessing the impact of violent crime, as measured by intentional homicide rates, on regional labour productivity growth.

Our analysis adopts a reduced-form approach, grounded in standard growth theory and, relying on a panel of annual data on the Italian regions, makes a number of contributions to the literature. Contrary to previous studies in the field, we adopt a flexible and efficient panel estimation approach, controlling for parameter heterogeneity, cross-section dependence and endogeneity. Our empirical methodology is based on mean-group estimation and multifactor modelling, making use of the standard mean-group (MG) estimator (Pesaran and Smith, 1995), as well as the multifactor modelling approaches proposed by Pesaran (2006) and Eberhardt and Teal (2012b) – respectively, the 'Common Correlated Effects Mean Group' (CCEMG) estimator and the 'Augmented Mean Group' (AMG) estimator. Following Eberhardt and Teal (2012a), we also deal with the issue of 'reverse causality' via Granger-causality methods. Our results strongly support the hypothesis that crime has significant negative effects on regional growth in Italy. According to a simulation-based exercise, over the 1970-2005 period some of the Southern regions lost on average between 0.35 and 0.8 percent a year in terms labour productivity growth because of higher-than-average crime rates.

As inherently reduced-form, the empirical analysis carried out in this paper is designed to examine aggregated outcomes directly and is, thus, not aimed at identifying the possibly complex

mechanisms characterising the relationship between criminal activity and economic growth. The evidence gathered suggests that a comprehensive investigation of these mechanisms may be key to the development of effective regional economic policies in Italy.

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Appendix

Table A1. ADF unit root tests on $\ln CR_t$

Region	*Code*	*Lags*	*Test Statistic*
Piedmont	PIE	0	-4.116**
Lombardy	LOM	0	-3.588*
Trentino-Alto Adige	TAA	0	-4.455**
Veneto	VEN	0	-5.263**
Friuli Venezia Giulia	FVG	0	-4.369**
Liguria	LIG	0	-3.825*
Emilia Romagna	EMR	0	-5.253**
Tuscany	TOS	0	-2.800
Umbria	UMB	3	-1.626
Marche	MAR	0	-7.173**
Lazio	LAZ	0	-4.572**
Abruzzo	ABR	0	-5.145**
Molise	MOL	2	-4.394**
Campania	CAM	2	-3.135^
Apulia	PUG	0	-2.233
Basilicata	BAS	4	-3.532*
Calabria	CAL	1	-3.729*
Sicily	SIC	0	-1.444
Sardinia	SAR	0	-4.650**

Notes: The small region Valle d'Aosta is considered as part of Piedmont (PIE). **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level. All ADF regressions include a constant and a deterministic trend. Lag selection performed via the sequential procedure proposed by Ng and Perron (1995).

Table A2. CCEMG and AMG extended model estimations: Specifications with CR_{it}

Estimator	CCEMG	CCEMG	AMG	AMG	AMG	AMG
Dependent variable	p_{it}	p_{it}	p_{it}	p_{it}	$p_{it} - \hat{\mu}_t^{\bullet}$	$p_{it} - \hat{\mu}_t^{\bullet}$
p_{it-1}	-0.141*	-0.169**	-0.305**	-0.316**	-0.341**	-0.338**
CR_{it}	-0.002**	-0.002*	-0.001	-0.002*	-0.000	-0.002*
k_{it}	0.328**	0.323**	0.0347**	0.335**	0.320**	0.309**
h_{it}	0.203	0.190	0.092	0.093	0.110	0.088
Common trend			0.899**	0.905**		
Intercept	0.003	0.005	0.037**	0.037**	0.038**	0.038**
# of region-specific trends significant at 10%		0		0		0

Notes: ** and * indicate, respectively, significant at the 1% and 5% level. Parameter estimates and standard errors were computed via the outlier-robust procedure in Hamilton (1991). h_{it} instrumented with second lag.

Table A3. CCEMG and AMG extended model estimations: Specifications with $\ln CR_{it}$

Estimator	CCEMG	CCEMG	AMG	AMG	AMG	AMG
Dependent variable	p_{it}	p_{it}	p_{it}	p_{it}	$p_{it} - \hat{\mu}_t^{\bullet}$	$p_{it} - \hat{\mu}_t^{\bullet}$
p_{it-1}	-0.138*	-0.143*	-0.299**	-0.307**	-0.336**	-0.326**
$\ln CR_{it}$	-0.007**	-0.008**	-0.005^	-0.007*	-0.004	-0.008*
k_{it}	0.335**	0.332**	0.350**	0.336**	0.319**	0.309**
h_{it}	0.165	0.158	0.121^	0.119^	0.136^	0.116
Common trend			0.897**	0.903**		
Intercept	0.003	0.005	0.001	-0.001	-0.005	-0.004
# of region-specific trends significant at 10%		1		1		2

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level. . Parameter estimates and standard errors were computed via the outlier-robust procedure in Hamilton (1991). h_{it} instrumented with second lag.

Table A4. *PLOSS* by region: Models with CR_{it}, ζ = -0.001

Region	*Code*	Cumulative *PLOSS*	Average annual *PLOSS*
Piedmont	PIE	-2.18	-0.06
Lombardy	LOM	-3.11	-0.09
Trentino-Alto Adige	TAA	-6.67	-0.19
Veneto	VEN	-7.41	-0.21
Friuli Venezia Giulia	FVG	-7.30	-0.20
Liguria	LIG	1.76	0.05
Emilia Romagna	EMR	-6.89	-0.19
Tuscany	TOS	-7.46	-0.21
Umbria	UMB	-7.57	-0.21
Marche	MAR	-9.32	-0.26
Lazio	LAZ	-1.97	-0.05
Abruzzo	ABR	-6.70	-0.19
Molise	MOL	-5.76	-0.16
Campania	CAM	12.58	0.35
Apulia	PUG	7.48	0.21
Basilicata	BAS	-0.95	-0.03
Calabria	CAL	28.99	0.81
Sicily	SIC	17.67	0.49
Sardinia	SAR	4.80	0.13