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# Does Crime Affect Economic Growth?

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## I. INTRODUCTION

Crime has a significant impact on the society. On one hand, criminal activity allows the consumption of illicit goods or services which could not otherwise be consumed. On the other hand, crime imposes great costs to the public and private actors, such as stolen and damaged goods, lost lives, security spending, pain and suffering. The estimation of such social cost of crime has become an important field of study in the last few decades (Czabanski, 2008), which shows how crime imposes a significant burden onto society. For example, Brand and Price (2000) estimate the total crime costs in Wales and England for the Home Office using survey data. They estimate a total expenditure equals to the 6.5% of the Gross Domestic Product (GDP). Anderson (1999) finds that the total annual cost of criminal activity in the United States accounts for 11.9% of the GDP. A recent work of Detotto and Vannini (2009) evaluates the burden of a subset of crime offenses in Italy (about 65% of all crime offenses) during the year 2006. The estimated total social cost exceeds the 2.6% of Italian GDP.

Although the identification and the estimation of crime costs have received wide attention in economic literature, the detrimental effect of crime to the (legal) economic activity is still neglected. Crime acts like a tax on the entire economy: it discourages domestic and foreign direct investments, reduces the competitiveness of firms, and reallocates resources, creating uncertainty and inefficiency.

A way to measure the crowding out effect of crime is to estimate its impact on the economic performance of the country or region. We can distinguish two approaches (Sandler and Enders, 2008). The first approach is to compare the overall economic performance of countries or regions with high level of crime to that of countries with low levels of crime, controlling for other explanatory

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variables. This approach descends from the cross-section models of economic growth in which the economic performance is regressed on a number of socio-economic variables (Barro, 1996).

In this framework we can consider the works of Mauro (1995), who shows a significant negative relationship between 'subjective corruption indices' and the growth rate among 70 countries in the early 1980s; Lambsdorff (2003), who finds that corruption reduces the capital productivity in a panel of countries; Forni and Paba (2000), who examine the impact of several socio-economic variables on the economic performance of the Italian provinces during the period 1971–1991; Peri (2004), who, using a larger data set (from 1951 to 1991), shows that the annual per capita income growth is negatively affected by murders after controlling for other explanatory variables; Pellegrini and Gerlagh (2004), who find that the impact of corruption on economic growth acts by reducing the ratio of investment to GDP and the country's openness; Cardenas (2007), who focuses on the relationship between crime and growth rate in an unbalanced panel of 65 countries during the period 1971–1999; Gaibulloev and Sandler (2008), who measure the impact of domestic and transnational terrorism[2] on income per capita growth for 1971–2004 in a panel of 18 Western Europe countries.

This approach allows working with a large amount of information for the key variables, such as per capita GDP or crime indexes; on the other hand, this approach is hampered by the data source problems, the cross-border spillovers effects, and the dynamic effect identification. Moreover, it suffers from the selection of countries (switching region the frequency and the importance of crimes change).

The second framework consists in the univariate and multivariate time series methodology. Recently, there have been many contributions to this approach, where crime is considered along with economic variables. Enders and Sandler (1996), employing a transfer function and a VAR model, assess the impact of terrorist incidents on net foreign direct investment in Greece and Spain. Masih and Masih (1996) estimate the relationship between different crime types and their socioeconomic determinants within a multivariate cointegrated system for the Australian case. Narayan and Smyth (2004) implement the Granger causality tests to examine the relationship among seven different crime typologies, unemployment and real wage in Australia within an AutoRegressive Distributed Lag (ARDL) model. Mauro and Carmeci (2007) empirically explore the link between crime, unemployment and economic growth using Italian regional data. Cardenas (2007) analyzes Colombia's annual GDP growth between 1951 and 2005. Habibullah and Baharom (2009), applying

2. Terrorism can be regarded as a special case of crime (crime against humanity). See Sandler and Enders (2008) for a survey of the literature on terrorism effects.

an ARDL model to the Malaysian case, analyze the relationship between real gross national product and different crime offences. Recently, Detotto and Pulina (2009) applied an ARDL model to the Italian data (1970–2004) to assess the relationship between several crime offences, deterrence indicators and economic variables. Chen (2009) implements a Vector AutoRegressive (VAR) model to examine the long-run and causal relationships among unemployment, income and crime in Taiwan.

The time series approach seems to have several advantages in terms of the interpretability of results and application, because it allows the identification of dynamic processes and the forecasting analysis. Moreover, it does not need to distinguish in advance the endogenous variables from exogenous ones. On the other hand, it needs a large number of observations (rarely available for crime variables) to guarantee the robustness of the estimators and the performance of the statistical tests. Furthermore, the choice of the economic model, in which to insert the crime variable, could affect the analysis; changing the explicative variables, the effect of crime on the economic growth will change.

To avoid this problem, we propose an autoregressive model, in which the GDP variations are explained by its past history and a crime variable; in practice we choose the best model which is able to explain the economic fluctuations and verify if a crime variable could explain more.

Moreover, we allow the variation along the time of the crime coefficient, using a state space model (see, for example, Harvey, 1989). This choice provides the measurement of the magnitude of the economic impact of crime on the society over time. In addition, this approach can answer more questions than a fixed parameter model. Firstly, if crime acts as a brake on the economic growth, is it for the whole period? Secondly, the evolution of the crime effect, detecting its trends, cycles or break-points can be analyzed. Furthermore, we can answer the following relevant questions: Do the wider economic distortions depend on the level of criminal activity? Is there a threshold beyond which any further increase in crime does not carry any wider economic distortions? Or is there a 'natural' level of crime, after which the negative effects occur? Does the evolution of the crime distortions display different behaviors in the different phases of the business cycles? Thus, the analysis could lead to important policy implications. First, it adds a useful component in evaluating the cost of crime. This aspect would allow the full understanding of the burden of crime, and the comparison with other social diseases. Furthermore, the analysis may become a useful tool to calibrate policies for combating crime. Indeed, when implementing a cost-benefit analysis, it may be convenient to increase the contrast level of crime when the economic cost of crime is greater.

We apply this model to the Italian case, for which a large data set with monthly frequency (from January 1979 up to September 2002) is available. Italy makes an interesting case study not only because it accounts for about one-tenth of all crime offences in the European Union (source Eurostat), but also, and especially, because Italian crime is historically characterized by a strong incidence of organized crime. Mafia, Camorra and 'Ndrangheta, along with other minor criminal organizations, strongly affect the economic performance of much of the country.

The paper is organized as follows. In the next section we present our model, which will be applied to the Italian data in section 3. In section 4 we propose an impulse response function analysis to evaluate the effects of crime on economy in the long period. Some remarks will conclude the paper.

## II. A STATE-SPACE MODEL FOR EVALUATING THE EFFECTS OF CRIME ON ECONOMY

As said in the introduction, to avoid the dependence on the model specification and to detect the effect of the crime on the economic growth, we propose a pure autoregressive (AR) model, with the variable representing the crime as the only explicative variable. The model is expressed by:

$$y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i y_{t-i} + (\bar{\beta} + \xi_t) c_{t-h} + w_t \tag{1}$$

where $y_t$ represents the first differences of the logarithms of the GDP at time $t \times 100$, whereas $c_{t-h}$ is the crime variable at time $t-h$; $h$ is the lag for which the crime manifests its effect on GDP growth (it is quite reasonable that the impact of crime on economic output appears with some time delay). The disturbance $w_t$ are Normally distributed with mean 0 and variance $\sigma^2$; $\alpha_i$ ($i = 0,1, \ldots, k$) are unknown AR coefficients. The coefficient of $c_{t-h}$ can be split in two parts: the steady state coefficient $\bar{\beta}$ and the variation with respect to $\bar{\beta}$ at time $t$, represented by $\xi_t$. In other words, the coefficient of the crime variable is time-varying, supposing that the crime effect can vary along the time. Hereafter, we will call this coefficient:

$$\beta_t = \bar{\beta} + \xi_t$$

The dynamics of $\xi_t$ is represented by:

$$\xi_t = \gamma \xi_{t-1} + v_t \tag{2}$$

where $v_t \sim N(0, v^2)$.

Equations (1) (*observation equation*) and (2) (*state equation*) constitute a particular kind of *state-space model* and can be easily estimated using the

*Kalman filter* to explicit the likelihood function to be maximized. The Kalman filter is an algorithm for calculating an optimal forecast of the value of $\xi_t$ on the basis of information observed through date t-1: for details on the Kalman filter and the state-space models we refer to Harvey (1989) and Hamilton (1994).

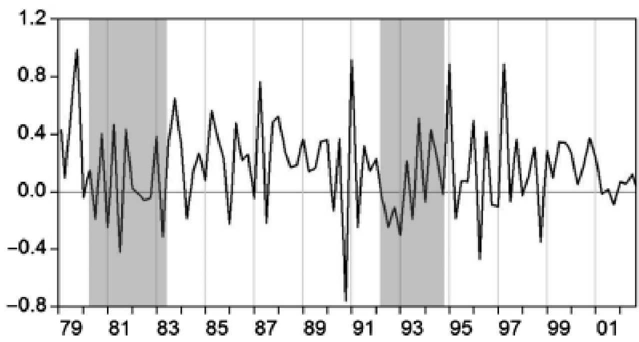
Before to conclude this section, we dwell upon a computational aspect. In (1) we prefer to use always AR processes and not more general and parsimonious ARMA processes, also when the order k is high. In fact the use of an ARMA process can create some difficulties in its identification; the 'general-to-specific' strategy is tricky in this case because different values of the parameters will yield the same likelihood function (Harvey, 1989, pp. 79). On the contrary, the AR processes are quite easy to estimate and specify, although they may sometimes require a large number of parameters.

## III. THE ITALIAN CASE

We apply model (1)-(2) to study the impact of crime on economic performance in Italy. We use monthly data of Italian GDP. Data refer to the period January 1979 - September 2002 (source ISTAT). The GDP series is expressed in real term and adjusted for the seasonal component; then it has been transformed to monthly frequency using the method proposed in Fernandez (1981). In Figure 1 the GDP fluctuation are shown, with the gray bars indicating the recession periods (detected by the Economic Cycle Research Institute-ECRI).

*Figure 1*

First differences of the logarithms of real monthly seasonally adjusted Italian GDP
Notes: The grey shadings present the recessions occurred in Italy during the period 1979–2002. The dating of the Italian business cycle is calculated by ECRI.



## 1. *The crime proxy*

An important task in estimating model (1)-(2) is the choice of a good indicator to represent the crime activity. The official crime data come from police reporting activity, and they suffer from the underreporting and underrecording bias (Mauro and Carmeci, 2007). In other words, official data represent only the tip of the crime iceberg. Moreover, in long period analysis we have to take into account the changes in reporting that come from technical innovations, police efficiency, depenalisation or, conversely, law intervention. Hence, we need a crime index that is sufficiently well reported by Police and has the same definition for all period considered.

Following Forni and Paba (2000), Cardenas (2007) and Mauro and Carmeci (2007), the number of recorded committed intentional homicides are used here as the crime activity indicator. The homicide rates are chosen for their highest reliability among all crime variables. Besides, a number of murder events are caused by mafia activity. In this sense, homicide incidents can be interpreted as a roughly indicator of organized crime activity.

Figure 2 shows the plot of the monthly totals of intentional homicides and the total crime offences over the 1979 through 2002 period. Notice that the two series track each other sufficiently well.

Table 1 shows the correlation statistics of murder series with the time series of the main crime offenses, namely robberies, drug offenses, fraud and total crime. The homicide rates appear to be well correlated to the other crime offenses,

*Figure 2*

Dynamics of homicide rate (left scale and continuous line) and total crime rate (right scale and dotted line)

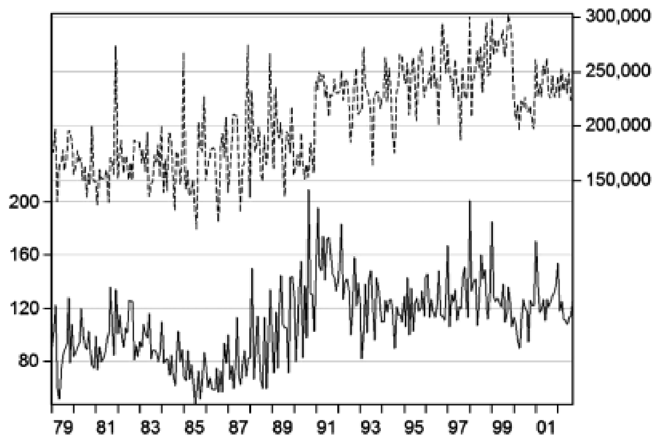


*Table 1*

Correlation of Some Crime Variables (Sample Period: January 1979- September 2002)

| | Total | Homicides | Drug offences | Thefts | Robberies | Fraud |
|---|---|---|---|---|---|---|
| Total | 1 | | | | | |
| Homicides | 0.603 | 1 | | | | |
| Drug offences | 0.702 | 0.640 | 1 | | | |
| Thefts | 0.887 | 0.593 | 0.526 | 1 | | |
| Robberies | 0.710 | 0.625 | 0.697 | 0.593 | 1 | |
| Fraud | 0.758 | 0.423 | 0.567 | 0.526 | 0.535 | 1 |

especially to the total crime offenses (the correlation coefficient is 0.60), the drug offenses (0.64) and the robberies (0.62).

## 2. *The crime effect*

Dealing with stationary processes, before estimating the model, we investigate the integration properties of the series LGDP (logarithm of GDP) and LHOM (logarithm of homicide rates) using the usual unit root tests. This analysis, detailed in appendix A, suggests to use, in (1)-(2), the differences of the logs of GDP as $y_t$ and the logs of the homicides as $c_t$. Moreover, this analysis evidences the presence of a break date in September 1990, which supports the use of a time varying parameter model. In fact, as pointed out by Harvey (1989, p. 308), when a time series is subject to a change of regime, a time varying parameter model can be more appropriate.

The last step we need to estimate model (1)-(2) is the choice of the lag $h$ with which the crime variable has effect on the real GDP variations. Following Enders et al. (1992) approach, we have tested different period lags for LHOM, and the model with $h = 3$ is found to be the best fitting model in terms of BIC.

The details about the estimation of the full model are presented in appendix B. Our interest mainly concerns the coefficients of crime. The coefficient $\bar{\beta}$ shows that, on average, a 1% increase in crime activity causes a monthly GDP reduction by 0.0004%, whereas the $\gamma$ parameter of the state equation is equal to 0.89, that indicates a certain persistence of the crime coefficient. In other words, the crime effect exhibits low variations along the time.

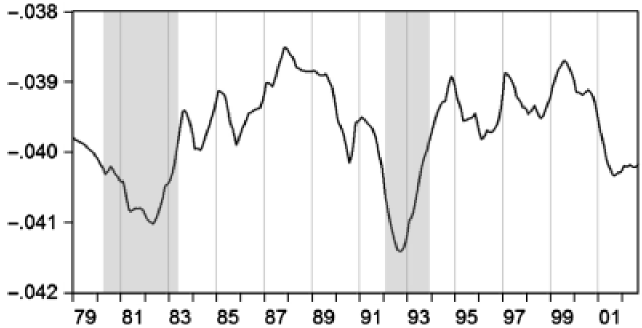
This is clear observing Figure 3 that shows the evolution of the smoothed estimation of $\beta_t$.[3] The coefficient varies with a cyclical behavior around the mean value $\bar{\beta}$. The impact of homicides rates on the real GDP growth in absolute terms is remarkably high in two periods (1980–1983 and 1992–1994)

3. The smoothed estimation is a by-product of the Kalman filter, which provides the estimation of the parameter conditional on the full information available.

*Figure 3*

Dynamics of the $\beta_t$ coefficient

Notes: The grey shadings present the recessions occurred in Italy during the time span 1979 up to 2002. The dating of the Italian business cycle is calculated by ECRI.




with a maximum in September 1992. Each $\beta_t$ is significantly different from zero with high probability, which means that the crime effect on GDP works on the full time span analysed.

Interestingly, $\beta_t$ is quite lowly correlated to the homicide rates ($r = -0.11$). This fact implies that the evolution of the crime effect cannot be explained by the crime trend, but it seems to follow a specific cycle. Moreover, this result, along with the low values of $\beta_t$, suggests that the economic costs of crime have a strong fixed component.

Remarkably, the impact of crime on real GDP growth seems to be more relevant during the recessions than the expansion periods. The average monthly GDP reduction due to crime is 0.00039% during expansions, and 0.00041% during recessions. Nevertheless their similar values, the size of the economic growth reduction is different during the two cyclical phases, as shown by the ANOVA F-test (= 357.67) and the Welch F-test (= 449.52) for equality of means. This is reasonable if we consider that the crime activity imposes a cost to the legal activity, and such a cost could be heavier during contraction regime. In other words, crime affects more when the economic growth slows down because they divert resources needed for economic recovery. Moreover, the marginal economic costs have the highest dependency on crime level during the slumps: calculating the correlation coefficient between $\beta_t$ and the murder rate, it is not significantly different from zero for the overall period and during expansion, whereas it is significant at 1% size (and equal to $-0.346$) during recession. In other words, changes in crime rates are perceived better when the economy is slowing, conditioning its growth opportunities.

Resuming, during recessions the economic costs are, on average, 5% more than during expansions. During a recession, one percent increase in crime activity leads, on average, to a reduction of monthly economic growth by 0.00041%. In monetary values, it accounts for about half a million of euros (base-year = 2006).

## IV. LONG RUN CRIME EFFECTS

The results illustrated before constitute a kind of short-run effect. Following Enders (1995, pp. 277–290), the impulse response function (IRF) is implemented to simulate the long-run effect of a one-percent shock in monthly crime.

In order to implement the IRF, we have to test for the exogeneity between the homicide rates and the GDP growth. If the murder rate is not exogenous, one shock in murders series would impact the economic growth, which in turn affects the homicide rate. In this way, the impulse response analysis should be performed with a dynamic system of equations to capture the effect in both directions. Why would the homicide variable be endogenous? As shown in the previous section, the murder rates are correlated to several types of crime offenses, such as burglaries or frauds. On one hand, it is reasonable to expect that an increase in criminal activity raises, directly or indirectly, the homicide rates, by increasing opportunities that may lead to the occurrence of murders. On the other hand, a vast literature shows how crime rates depend on the business cycle. Hence, the economic growth may impact, although indirectly, the homicide rate. In order to establish the exogeneity of homicide rates, a Granger causality test is implemented and the statistic test is not significant at 5% level (F-statistic = 0.606). The null hypothesis is the absence of Granger causality, which implies the strong exogeneity of the variable of interest (Maddala, 1992, pp. 325–331). The null hypothesis cannot be rejected: DLGDP does not Granger-cause LHOM, so the homicide rate does not seem to respond to variations of the real economic growth. More evidence for exogeneity can be obtained applying the Hausman test.

A version of the Hausman test proposed by Davidson and MacKinnon (1989, 1993) is used. In practice two OLS regressions are run. In the first regression, the variable suspected to be endogenous, namely homicides, is regressed on all exogenous variables and the instrument, and the residuals are retrieved; then in the second regression, the original (linear) model is re-estimated including the residuals from the first regression as additional regressors.

Finding an instrument variable for homicide rates is not trivial. Murder is a type of violent crime whose determinants can be divided into two groups. On one hand, as explained earlier, the economic variables, such as business cycle, employment rate and income distribution, directly or indirectly affect the murder rate. On the other hand, socio-demographic variables, such as cultural aspects, urbanization, modernization, demographic structure, play a significant role in explaining the rate of homicides. Then, our goal is to identify an instrumental variable that depends mostly from socio-cultural variable instead of economic ones. Obviously, it is known that the economic and socio-cultural variables affect each other, but we expect that they need a long period of time so that the effect takes place.

After analyzing all crime cases, the sex assault rate was chosen; this offense is largely related to cultural aspect and social phenomena, such as the role of women in society, urbanization and civilization, and it does not seem to be correlated with the economic cycle in the short run. The correlation between the seasonally adjusted series of sex assaults and murders is sufficiently high (0.58), while the one between sex assault and GDP growth rates is low ( − 0.10). Moreover, the correlation between the instrumental variable and the residuals of the linear model is not significantly different from zero.

Sex assaults seem to offer a good instrument for murder rate; hence, the Hausman test can be implemented. In the first stage, the coefficient of the instrumental variable, namely the three month lagged sex assaults, is significant. In the second step, the coefficient on the first stage residuals is not significantly different from zero. This result indicates that we could not reject the null hypothesis of exogeneity of homicide variable.

Hence, treating the homicide rate as an exogenous variable, we implement the IRF as in Enders et al. (1992). As Figure 4 shows, after a three-period delay, the GDP growth declines and then returns to its initial value in a few months. Discounting all subsequent GDP losses, it is possible to evaluate the cumulative value of a one percent crime shock, for recession and growth periods separately.

*Figure 4*

Italy's wider economic distortions of crime (GDP growth response to an increase of crime by 1%)

During a recession (expansion), a rise in crime by 1% causes, on average, a change by −0.00022% (−0.00021%) in annual GDP growth, which corresponds to a reduction of 2.6 million euros (2.4 million euros) in a year. In practice, the long run crime costs are 5% higher during recession than expansion.

## V. REMARKS

We have proposed a state space model to analyze the effects of crime on economic growth and we have applied this methodology to the Italian data. The model seems able to answer several questions, that are relevant in the study of the effects of criminality on the economy. We recall the questions made in section 1, and resume the findings emerging from our study:

1. *If crime acts as a brake on economic growth, is it for the whole period?* The results confirm that crime negatively impacts the economic performance; this may happen through several channels: crime discourages the investments, reduces the competitiveness of the firms, and reallocates the resources creating uncertainty and inefficiency. Our model shows that the entire sample period is affected by an economic cost, which can be deduced by Figure 3. On average, a rise in crime rates by 1% reduces the real economic growth by 0.00040% in a month. Furthermore, the findings suggests that the economic costs of crime exhibit a very significant fixed component.
2. *Does the wider economic distortions depend on the level of criminal activity?* We have shown that the correlation between the time-varying effect of the crime and the murder rate is not significantly different from zero, so it seems that there is no relationship between the marginal impact of crime and its level.
3. *Is there a threshold beyond which any further increase in crime does not carry any wider economic distortions? Or is there a 'natural' level of crime, after which the negative effects occur?* Figure 3 shows that the dynamics of the economic cost of crime is time-varying but always significant. Hence, it seems that there is not a threshold value.
4. *Does the evolution of the crime distortions display different behaviors in the different phases of the business cycles?* We show that the wider economic distortions of crime are not constant over time and have an asymmetric effect in growth and recession periods. Specifically, the negative impact of crime on Italian economic performance is 5% stronger during the recessions than the expansions. Moreover, through the IRF analysis, we have obtained that, during the economic contractions, a one percent increase in crime rates causes, on average, a reduction in the real economic

growth by 0.00041% in a month and by 0.00022% in a year, which is equal to 0.5 and 2.6 million of euros, respectively.

Finally, the analysis seems to suggest the presence of a cyclical component in the crime effects, strictly related to the economic business cycle. It would be interesting for future research to investigate this aspect.

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## APPENDIX A: PRELIMINARY ANALYSIS

In order to identify the integration order of LGDP and LHOM, we have applied the Augmented Dickey Fuller (ADF), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Phillips Perron (PP) tests. The results are shown in Table 2. LGDP is found to be stationary in the first difference, whereas the unit root tests for LHOM seem to be inconclusive. The PP test indicates LHOM is stationary, while ADF and KPSS test cannot reject the null hypothesis of unit root. It is important to note that the presence of a shift in the level of the series can reduce the power of the unit root tests if the shift is ignored (Lanne et al., 2002). More precisely, the unit root tests 'are biased toward the nonrejection of

*Table 2*

Unit Root Tests.

| Variable | ADF | lags | KPSS | lags | PP | lags | Period | MADF | lags |
|---|---|---|---|---|---|---|---|---|---|
| LGDP | − 2.053 | 11 | 0.274*** | 14 | − 1.552 | 2 | 1/79-9/02 | | |
| DLGDP | − 3.451** | 10 | 0.221 | 3 | − 4.825*** | 71 | 1/79-9/02 | | |
| LHOM | − 2.072 | 5 | 0.159** | 13 | − 12.242*** | 11 | 1/79-9/02 | | |
| LHOM | − 2.872* | 3 | 0.25 | 8 | − 8.566*** | 7 | 1/79-8/90 | | |
| LHOM | − 9.827*** | 0 | 0.415* | 7 | − 10.346*** | 6 | 9/90-9/02 | | |
| LHOM | | | | | | | 1/79-9/02 | − 3.136** | 5 |

Notes: (1) All critical values for rejection of null hypothesis of a unit root are tabulated in MacKinnon (1996), except the critical values of URSB, which are tabulated in Lanne et al. (2002); (2) ***,** and * indicate statistical significance at the 1% 5% and 10%, respectively; (3) D denotes the first difference operator; (4) The number of lags in ADF and URSB tests are set upon BIC criterion, in KPSS and PP tests upon Newey-West bandwidth; (5) The break date considered in URSB test is September 1990; (6) All variables are expressed in natural logarithm.

a unit root' (Enders, 1995, p. 243). Featuring a break date in September 1990, the series is divided in two parts and we perform the unit root tests in each portion. Both components seem to be stationary, even if 'the power of this tests is reduced due to the smaller sample sizes' (Kirchgässner and Wolters (2008), p. 176). Hence, we test the presence of a structural break in the series, identified using the procedure proposed by Lanne et al. (2001); then we apply the modified ADF (MADF) test, as proposed by Saikkonen and Lütkepohl (2002) and Lanne et al. (2002).

As described in the last row of Table 2, the unit root test with a level shift is performed. The unit root statistic test is − 3.136, that allows us to refuse the null hypothesis of absence of stationarity at 5% level. The critical values used here are tabulated in Lanne et al. (2002).

## APPENDIX B: ESTIMATION AND VALIDATION OF THE MODEL

The model identified is applied to study the effect of crime on the economy in Italy, using the differences of the logs of GDP as $y_t$ and the logs of the homicides as $c_t$ and $h = 3$. The autoregressive order $k$ was selected using a BIC criterion on a linear model (1) with $\xi_t = 0$ for every $t$.[4] This procedure provides $k = 14$.

The maximization of the likelihood was performed using the Berndt, Hall, Hall, Hausman (BHHH) optimization algorithm. An important computational task is constituted by the choice of starting points of the Kalman filter recursion. Clearly, the numerical optimization methods work better if the starting values are chosen from a close neighborhood of their true vales (Zivot et al., 2004, p. 32). Unfortunately, how to identify an appropriate starting value

4. The linear model explains the 92.6% of the variance of $y_t$.

*Table 3*

Estimation Results and Diagnostic Statistics for the State-Space Model (Standard Errors in Parentheses).

| Parameters Estimation | | | | |
|---|---|---|---|---|
| $\alpha_0$ | $\alpha_1$ | $\alpha_2$ | $\alpha_3$ | $\alpha_4$ |
| 0.222 | 1.767 | − 0.807 | − 1.721 | 3.041 |
| (0.020***) | (0.096***) | (0.158***) | (0.138***) | (0.156***) |
| $\alpha_5$ | $\alpha_6$ | $\alpha_7$ | $\alpha_8$ | $\alpha_9$ |
| − 1.378 | − 1.562 | 2.744 | − 1.247 | − 1.016 |
| (0.179***) | (0.162***) | (0.176***) | (0.152***) | (0.153***) |
| $\alpha_{10}$ | $\alpha_{11}$ | $\alpha_{12}$ | $\alpha_{13}$ | $\alpha_{14}$ |
| 1.772 | − 0.808 | − 0.391 | 0.673 | − 0.308 |
| (0.147***) | (0.123***) | (0.115***) | (0.084***) | (0.045***) |
| $\bar{\beta}$ | $\gamma$ | $\sigma^2$ | $v^2$ | |
| − 0.040 | 0.895 | − 5.558 | − 14.105 | |
| (0.004***) | (0.370**) | (0.121***) | (7.980*) | |
| Diagnostic Statistics | | | | |
| $LB_{24}$ | In-sample RMSE | DM | Out-of-sample RMSE | DM |
| 22.32*** | 0.062/0.063 | 2.443** | 0.043/0.105 | 4.036*** |

Notes: (1) ***,** and * indicate significance at the 1%, 5% and 10%, respectively; (2) $LB_{24}$ is the Ljung-Box statistic at lag 24; (3) in sample and out of sample RMSEs compare the RMSE of the time varying parameter model against the RMSE of the linear model; (4) DM is the Diebold-Mariano statistic.

for the unknown parameters of a state space model is still an open question in literature. Following Hamilton's (1994, p. 3057) approach, the OLS estimates are used as starting values of $\alpha_0, \ldots, \alpha_{14}$ and $\bar{\beta}$. Then, we impose the starting values of $\sigma^2$ and $v^2$ equal to one. For what concerns the $\gamma$ coefficient, we do not have any ex-ante information about this value; we use a simple grid approach with 0.01 increase in the parameter and we select the model in correspondence of the minimum value of BIC.

Table 3 reports the estimated coefficients of our state space model and some diagnostic statistics. The Ljung-Box statistic shows a clear evidence in favor of the hypothesis of autocorrelation. Also, the goodness of fitting and prediction of the time varying parameters model and the fixed parameters model are evaluated. The RMSE (root mean square error) of the in-sample and out-of-sample one-step ahead forecasts is calculated in both models (bottom of Table 3). The in-sample forecasting evaluates the goodness of fit of the model in the full data set, while the out-of-sample forecasting indicates the ability of a given model to predict future values.[5] The RMSEs are compared with respect to the RMSEs of the corresponding linear model without time varying parameters; we can note that they are fewer in the case of time varying parameters model, especially for the out-of-sample forecasts, and the modified Diebold-Mariano

5. We have re-estimated the model excluding the last 21 observations, which are used to compare the forecasts.

test (Harvey et al., 1997) rejects the null hypothesis of equal RMSE. Hence, we can conclude that the time varying parameters model performs better than the fixed parameters model.

## SUMMARY

Criminal activity acts like a tax on the entire economy: it discourages domestic and foreign direct investments, it reduces firms' competitiveness, and reallocates resources creating uncertainty and inefficiency. Although the impact of economic variables on crime has been widely investigated, there is not much concern about crime also affecting the overall economic performance. This work aims to bridge this gap by presenting an empirical analysis of the macroeconomic consequences of criminal activity. Italy is the case study for the time span 1979–2002. Dealing with a state space framework, a time varying parameter approach is employed to measure the impact of criminality on real Gross Domestic Product along time, and to measure the asymmetric impact in recession and expansion periods. The analysis is completed evaluating the effects of crime fluctuations in the long period by an impulse response analysis.