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DOES MORE CRIME MEAN FEWER JOBS? AN ARDL MODEL

Claudio Detotto
Manuela Pulina

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CRENoS - SASSARI
VIA TORRE TONDA 34, I-07100 SASSARI, ITALIA
TEL. +39-079-2017301; FAX +39-079-2017312

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ViaIsMirrionis,1
09123Cagliari
Tel./Fax070291201
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Does more crime mean fewer jobs? An ARDL model

Claudio Detotto, Manuela Pulina[1]

DEIR (Università degli Studi di Sassari) and CRENoS

Abstract

This paper analyses how a set of economic variables and a deterrence variable affect criminal activity. Furthermore, it highlights the extent to which crime is detrimental for the economic activity. The case study is Italy for the time span 1970 up to 2004. An Autoregressive Distributed Lags approach is employed to assess the cointegration status of the variables under investigation. A Granger causality test is also implemented to establish temporal interrelationships. The main finding is that all crime typologies, but homicides and fraud, have a crowding-out effect on legal economic activity, reducing the employment rate.

Keywords: Crime, deterrence, economic variables, crowding-out effect.

JEL Classification: K14, C32, E24

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[1] **Corresponding author** - DEIR, Università degli Studi di Sassari, via Torre Tonda 34, 07100 – Sassari (Italia), mpulina@uniss.it

1. Introduction

Criminal activity can impose great costs to the public and private actors. Crime activity can lead to both direct and indirect costs for a society: the former are derived from the value of lost lives, damaged goods, lost wages, reduced trade activity; the second type of costs are for example higher insurance premiums, increased levels of security (e.g. housing and public building alarm systems, more police forces); these costs can have detrimental effects on domestic and foreign direct investments, employment and economic growth (Sandler and Enders, 2005).

From an economic perspective, a criminal offender can be viewed as a rational individual that maximises his/her utility allocating his/her time between legal and illegal activities given a budget constraint. In the decision making process, a potential offender will compare costs and benefits derived from a criminal act. As Becker (1968) points out, a rational offender will carry out an illegal activity if the marginal benefit deriving from crime, discounted by the expected value of the penalty, is higher than the marginal benefit deriving from a legal activity, *ceteris paribus*.

However, the level of crime in a country does not depend only on criminals' rationality, attitude towards risk and preferences but also on several economic, demographic and sociological factors, given that individuals tend to respond to incentives. For example, an economic expansion could be beneficial to reduce criminality but favourable economic conditions can also trigger higher levels of illegal activity; on the contrary, economic turmoil can induce more individuals to commit a criminal activity such as theft or robbery. Law enforcement can also have an important impact on crime. For instance, with longer average time served in prison and higher probability of punishment less criminal acts might be perpetrated. Sociological and demographic factors such as the level of social cohesion, family disruption, immigration, education, gender and age might influence criminal activity.

Entorf and Spengler (2004) notice that economic crime research is still limited in Europe. As far as Italy is concerned, an increasing number of empirical studies are available in the economic crime literature (e.g. Marselli and Vannini, 1997; Buonanno, 2003; Mauro and Carmeci, 2007).

Italy makes an interesting case study not only because it accounts for about 10% of all crime offences in the European Union (Eurostat, 2006), but also, and especially, because Italian crime is historically specialized in property crimes (such as theft and robbery), where the economic motivations might play a significant role, while violent offences (such as homicide and assault) are much less common with respect to other European countries. Italy is also an important case study because a consistent number of murders is done by organized crime, such as Sicilian mafia, Camorra and 'Ndrangheta, mainly for economics reasons. These features might be of interest in designing an economic model of crime, testing to what extent socio-economic variables influence crime in Italy, both in the short and long run.

The present empirical study is based on the empirical work proposed by Narayan and Smyth (2004) that analyse male youth unemployment and real income as determinants of crime rates in Australia. An AutoRegressive Distributed Lags (ARDL) cointegration analysis is adopted and a Granger causality test highlights temporal relationships between the variables under investigation.

In the current paper, an investigation on the dynamic relationship amongst six main crime typologies *(i.e.* number of recorded thefts, homicides; robberies, extortions and kidnapping; fraud; crimes against property; and total crime) and a set of socioeconomic determinants in a multivariate framework is pursued. The case study is Italy and an annual frequency is used from 1970 up to 2004. As a first step of the research a general-to-specific methodology is run in order to reach a more parsimonious specification based upon information criteria, diagnostic tests and statistically significant coefficients. In this manner, it is possible to choose parsimoniously those factors that influence crime. Hence, an autoregressive distributed lags approach is employed to assess the integration and cointegration status of the variables under investigation. As discussed later in the paper, rather than using Johansen's approach, this framework allows one to run a more robust testing procedure with a small sample size and at the same time it assumes an endogeneity condition amongst the variables under investigation unlikely the Engle and Granger procedure.

The main questions are the following:

- Do socio-economic variables affect crime in Italy?
- Are there significant differences that emerge when employing different economic variables to analyse crime? As Baharom and Habibullah (2008) point out (quoting a previous study by Chrisholm and Choe, 2005) "there is ambiguity in the empirical studies of crime economics regarding various income variables used to proxy the expected net gains from crime and as a result empirical findings are often mixed or contradictory to one another" (p. 1). Scorcu and Cellini (1998), for example analyse the

relationship between economic variables and crime in Italy. Within a bivariate framework, they show that homicides and robberies can be better explained by consumption, whereas thefts can be better explained by unemployment. Hence, in light of this literature ambiguity, one of the main contributions of the present study is to give a comprehensive empirical investigation of the underlying economic factors, measured by three economic variables, namely the per capita real GDP, the real output and per capita real income, that are assumed to contribute to the different crime patterns. However, only best models outcomes are reported in this paper (though full results can be provided upon request).

- Is criminal activity detrimental for legal activity? As Sandler and Enders (2005) point out, economic upturns and downturns can be thought of as consequences as well as root causes of crime. Besides, though the first hypothesis has been mostly proven in the literature, the second hypothesis has been mainly investigated via a Granger causality analysis. Hence, this paper goes a further step forward by employing the economic determinants of interest (*i.e.* income and employment) as dependent variables.
- Are there specific government acts that can influence criminal activity? Across the three decades under investigation, several governments interventions have occurred, such as amnesties, de-penalisations, pardons and structural reforms. The question is whether these law acts have affected certain crime typologies.

The paper is structured as follows. In the following section a review of the most recent studies is provided. In the third section an account on data and methodology employed is given. In the fourth section, empirical results emerging from the ARDL model, Vector Error Correction Mechanism (VECM) and Vector AutoRegressive (VAR) modelling, Granger causality testing analyses are reported. Conclusions are provided in the last section.

2. A literature review

This section is aimed at giving an account on the literature related to the analysis of the interrelationship between economic variables and criminal activity.

A new field of analysis on criminal activity and economics stems from the seminal work by Fleisher (1963), which investigates the effect of unemployment on juvenile delinquency. Some years later, Becker (1968) sketches the first criminal choice model, where the criminal is

hypothesised as a rational agent that maximizes his/her individual utility given his/her budget constraint.
Since then, many scholars have studied which variables affect criminal agents' choices and behaviour: unemployment (Witt et al., 1998; Raphael and Winter-Ebmer, 2001; Marselli and Vannini, 2000), inequality (Kelly, 2000; Choe, 2008), business cycles (Pyle and Deadman, 1994), education (Freeman, 1994; Lochner, 1999; Usher, 1997), social capital (Buonanno et al., 2006), weather (Field, 1992; Jacob et al., 2004), abortion (Donohue III and Levitt, 2001), social interaction (Patacchini and Zenou, 2005) and many other variables (see Buonanno (2003) for a survey of the literature on crime determinants).
Although the analysis of crime determinants has received wide attention in economic literature, the role of criminal activity as an explanatory variable is still much neglected. To this respect, crime can be viewed as a relevant activity that might have an impact on economic performance and economic agents' decisions, but to date there are still very few works that have as main objective the investigation of the effects generate by crime on economic activity.
The first contribution in this field is given by the use of the "rule-of-law" variable, proposed by Knack and Keefer (1995), in a number of growth model regressions (Barro, 1996; Sala-i-Martin, 1997).
Mauro (1995) finds a significant negative relation between "subjective corruption indexes" and the growth rate among 70 countries in the early 1980s. Del Monte and Pagani (2001), by implementing several dynamic panel data approaches to the Italian Regions, show two distinct negative corruption effects: the first one on private investment and the second one on the efficiency of public expenditures on infrastructure.
Pshisva and Suarez (2006) identify the negative impact of ransom kidnappings on investment in Colombia. Daniele and Marani (2008) analyse the effect of crime on foreign direct investment (FDI) in Italy using province data. They found that extortions and the presence of organized crime reduce FDI flows. De Mello and Zilberman (2008), using local Brazilian data, assess how property crime induces more savings.
Following Barro literature, Forni and Paba (2000) examine the impact of a number of socio-economical variables on the economic performance of the Italian provinces during the period 1971-1991. They consider growth not only in terms of income, but also in terms of employment and population. Their results indicate that murders, used as an index of organized crime activity, strongly affect employment growth. Based on Forni and Paba results, Peri (2004) considers a larger Italian provinces

dataset (1951 - 1991). He shows that the annual per capita growth and the annual employment growth are negatively affected by murders after controlling for other explanatory variables.

Recently, Cardenas (2007) analyzes Colombia's annual GDP growth between 1951 and 2005. He identifies the causes of the prolonged deceleration in growth observed in the country during the past two decades. Using the standard sources-of-growth-decomposition, he indicates that the deceleration of economic growth is the result of a reduction of productivity. The results of a VAR approach and the Granger causality tests suggest the presence of a causal relation from drug trafficking to violent crime, and from violet crime to productivity. Finally, the author focuses on the relationship between crime and growth rate in an unbalanced panel of 65 countries between 1971 and 1999. The results indicate that a one percent increase in criminality, namely homicide, leads to 0.003% reduction in growth rate of GDP per capita by decade.

In a recent paper, Burdett et al. (2006) present a theoretical model in which crime and economic variables, namely unemployment and inequality, are endogenous. This approach allows one to highlight the interactions amongst the variables and to consider some general equilibrium properties. More specifically, the model describes the link between crime and unemployment in both directions that imply the possibility to have multiple equilibria.

Mauro and Carmeci (2007) empirically explore the link between crime, unemployment and economic growth using Italian regional data. The results of the ARDL model, within a panel data framework, suggest that crime has a negative long-run effect on output level rather than on output growth.

Masih and Masih (1996) estimate the relationship between different crime types and their socioeconomic determinants within a multivariate cointegrated system for the Australian case. Within a Granger test framework, the authors establish the direction of the temporal causation between the variables, but they fail to find a crime impact on the socioeconomic variables under study.

Narayan and Smyth (2004) implement the Granger causality to examine the relationship between seven different crime categories, unemployment and real wage in Australia within an ARDL model. They found that in the short run robbery and stealing Granger cause real income while robbery and motor vehicle theft Granger cause unemployment. In the long run, income is Granger caused by unemployment, homicide and motor vehicle, whereas fraud is Granger caused by real income and unemployment.

Habibullah and Baharon (2008), applying an ARDL model to the Malaysian case, analyse the relationship between real gross national product and different crime offences. The results indicate that the long run causal effect in all cases runs from economic performance to crime rates and not viceversa. In a further paper, Habibullah and Baharon (2008) employ an ARDL model to test the Granger causality between income inequality and several crime offences in Malaysia. The authors fail to find any effect, either in the long-run or in the short-run, in either direction (that is from crime to income inequality and *viceversa*).

3. Data and methodology

In this paper six crime typologies are employed: number of recorded thefts (*RB*), number of recorded attempted or committed intentional homicides (*H*), number of recorded robberies, extortions and kidnapping (*SAK*), number of recorded fraud (*F*), number of recorded crimes against property (*TCP*) and finally total number of recorded crimes (*TC*); all these variables are defined per 100 thousands inhabitants. A preliminary investigation has involved a general-to-specific modelling approach in order to choose a set of economic (e.g. per capita gross domestic product, per capita real output, per capita real income; employment; national consumption), demographic (e.g. quota of women, age ranges), sociological (e.g. education, divorces) and deterrence variables (e.g. unknown offenders, average length of time served in prison by crime typology) based upon their statistical significance as well as on a *priori* interpretation belief. Following such a more rigorous procedure, the key determinants of each crime typology can be identified (Hendry, 1995). All the variables under study have been transformed in a natural logarithmic specification (*L*), assuming the existence of a non-linear relationship. An Ordinary Least Squares (OLS) approach can then be employed. The functions under investigation are the following:

1) LRB = f (LURB, LY, EMP)
2) LH = f (LUH, LPR, LEM)
3) LSAK = f(LUSAK, LPR, LEM)
4) LF = f(LUF, LY, LEM)
5) LTCP = f(LUTCP, LPR, LEM)
6) LTC = f (LTC, LPR, LEM)

where, *LRB, LH, LSAK, LF, LTCP* and *LTC* are the previously defined crime variables. *LURB, LUH, LUSAK, LUF, LUTCP* and *LUTC* are the ratio between the number of recorded crimes committed by unknown offenders and all recorded crimes in a given category (*LUNK*, as in Tables 3, 4 and 5); these variables are a proxy of the deterrence effect stemming from the criminal investigation efficiency of the local police force and from their knowledge of the local underworld (Marselli and Vannini, 1997); the expected sign of their coefficient is positive. *LY* and *LPR* are the per capita real income and output respectively; the expected sign is either positive, if an economic expansion causes an increase in crime (the wealthier a society the higher the crime level), or negative if an economic expansion causes a decrease in crime (the wealthier a society the lower the crime level). A crime crowding-out effect on legal economic activity is also tested and the expected sign for the coefficient of the crime variable is negative, that is, crime levels are higher the lower the economic growth employed as the dependent variable. Finally, *LEM* is the quota of employed active population; the expected sign is either positive or negative. In general, we expect a higher level of employment to lead to a crime reduction; however, it could be also true that in areas with higher levels of employed people a higher number of crimes is committed. In the case of Italy, Marselli and Vannini (2000) show that an increase in the unemployment rate drives more homicides, thefts and robberies. As a novel implementation, the impact of crime on employment rate is also tested and the expected effect is negative, that is, illegal and legal activities are presumed to be substitutes.

All data used in this paper are obtained from *Istituto Nazionale di Statistica* (ISTAT).

Data are aggregated at the Italian national level, using annual frequency from 1970 up to 2004.. An AutoRegressive Distributed Lags (ARDL) model is commonly employed in a time series analysis when the number of observations available are relatively small. One of the problems with employing a relatively low number of observations (in this case 33 data points) is to establish the order of integration of the variables under investigation. However, Pesaran *et al.* (2001) propose a method to test for cointegration irrespective of whether the variables under investigation are stationary in the level, I(0), or stationary in their first difference, I(1). By applying the Augmented Dickey Fuller (ADF) and Phillips Perron (PP) test, all variables are I(0) but *LH, LTCP, LEM* and *LUF*, which are found to be stationary in the first difference (Table 1). The second phase of the analysis involves testing for a long run relationship amongst the variables reported in functions (1) – (6). To this aim, an ARDL representation is followed (see Pesaran *et al.*, 2001 for a greater detail)

4. Empirical results

As a first step of the analysis, the cointegration test outcome is given. As a further step results on either a VECM or a VAR specification are specified. Finally, a Granger causality analysis is run to investigate the temporal relationships amongst the variables of interest.

4.1 Cointegration and empirical results

The cointegration test results are provided in Table 2. For all the empirical models, where the crime variables are employed on the left side of the equation, no cointegrating relationship is found. The next step of the investigation consists in running a VAR where the variables are treated as either I(0) or I(1), according to the ADF and PP unit roots test. Table 3 provides the main empirical findings derived from the static solution (the dynamic results can be provided upon request).

For the first model (*LRB*) an ARDL(1,3,2,3) is estimated based upon the AIC criterion; the diagnostics show an overall goodness of fit with no problems in the residuals, with the only exception for some heteroschedasticity detected at 5% (this outcome is not uncommon in ARDL models, see for example Pesaran *et al.* 2001). In this case, all variables of interest are statistically significant. Specifically, an increase in lack of deterrence by 1% causes an increase in thefts by more than 17%. On the one hand, a positive change in employment growth by 1% negatively effects this typology of crime, with a decrease of approximately 13%. On the other hand, an increase in the per capita real income causes a decrease in thefts of almost 3%. Hence, these findings support the idea that economic growth can help reducing thefts in Italy.

An interesting finding relates to the effects of crime on legal activity (Table 5). An increase in thefts by 1% determines a decrease in employment growth by 0.04%. This result is in line with the belief that being arrested reduces the probability to be employed (Narayan and Smyth, 2004). Besides, this outcome is also congruent with Becker's economic model where rational agents trade off between legal and illegal activity, leading to a substitution between working time and crime.

Model 2 relates to the number of homicides per 100 thousands inhabitants (*LH*). Following the unit roots test, *LH* and *LEM* are treated as I(1), whereas *LUH* and *LPR* are included in the level (being I(0)). A VAR is run accordingly and Table 3 shows the static solution results; the residuals show a good fit. The only statistically significant outcome is that an increase in employment growth by 1% causes a 2.7% increase in homicides growth. This outcome is in line with the belief that areas characterized by a higher level of employment might experience higher levels of violent crimes.

However, evidence is provided that this type of crime is detrimental for economic activity. When treating *LPR* as the dependent variable (Table 4), a growth in homicides by 1% causes a decrease in real production by 0.06%; hence a crime crowding-out effect is supported. Nevertheless, as reported in Table 5, *DLH* positive effects the employment growth (*DLEM*).

Turning to the number of recorded robberies, extortions and kidnapping (*LSAK*) as a function of the deterrence variable (*LUSAK*), per capita real output (*LPR*) and employment change (*DLEM*), Table 3 shows the static solution results. Notably, a lack of deterrence enhances this type of crime: if *LUSAK* increases by 1% *LSAK* raises by 3.5% on an annual basis. *LPR* is the only economic variable statistically significant; an increase in per capital real output by 1% determines an increase of *LSAK* by 1.3%.

From Table 5, a negative relationship emerges between *LSAK* and *DLEM* when using the latter as the dependent variable. Overall, an increase by 1% in this type of crime determines a decrease in employment growth by 0.05%. This outcome is in line with the previous finding for *LRB*.

In Model 4 the fraud variable (*LF*) is employed as the dependent variable. The preliminary findings showed as the per capita real income (*LY*) is the appropriate determinant. The residuals are a white noise and normally distributed; however, some signs of heteroschedasticity are present at the 5% level. From the static solution findings, a negative relationship is detected for *LY* showing that an increase in national wealth by 1% reduces this crime typology by 2.4% (Table 3). *LF* positively effects the employment growth (*DLEM*) (Table 5). This outcome is consistent with the belief that fraud is also committed by employees, as this type of criminal act is often hidden under legal activities.

In Model 5 *LTCP* (number of recorded crime against the property) is employed as the dependent variable in its level. From the unit roots test a mixed evidence emerges on the integration status of this variable (see Table 1). Nevertheless, a preliminary investigation has shown that treating *LTCP* as I(0) outperforms the model that includes *LTCP* as I(1), and detects no problems in the residuals. Table 3 highlights an expected positive relationship between the lack of deterrence (*LUTCP*) and this crime typology: the coefficient denotes an increase by 7.3% *ceteris paribus*.

In addition, an increase in per capita real output by 1% leads to a decrease in the number of crimes against property by 2.8% per year.
Tables 4 and 5 report the dynamics between *LTCP* and *DLEM*. Once more, a negative relationship is detected between these two variables; specifically, a rise in crime against property by 1% reduces the real output by 0.7% and the employment rate by 0.04%.
As a final step of the investigation, total number of recorded crimes (*LTC*) are taken into consideration (Model 6). Best results are achieved when employing *LUTC*, *LPR* and *DLEM* as explanatory variables. Hence, a VAR is run following the ADF and PP outcomes (Table 1), and no problems are detected in the residuals. The static solution is reported in Table 3. The *LUTC* coefficient has the expected positive sign, hence an increase by 1% of the quota of recorded crimes committed by unknown offenders causes a rise in overall crime by the same magnitude. Besides, an increase by 1% of the national output leads to an increase in total crime by 0.4%.
As a further result, the coefficient of the first lag of the cointegrating vector depicts the expected negative sign (Table 4). The negative relationship between crime and employment rate is also confirmed. A rise in total crime by 1% causes a decrease in the employment growth by 0.05% *ceteris paribus* (Table 5).
As a matter of fact, Table 3 shows the existence of specific effects that require the inclusion of dummy variables (*i.e. D91* takes the value one in the year 1991 and zero otherwise; *D98* takes the value one in the year 1998 and zero otherwise; *D00* takes the value of one in the year 2000 and zero otherwise). The first qualitative variable (*D91*), that effects thefts (*LRB*) and homicides (*DLH*), is possibly picking up the positive effect produced by the introduction of the new criminal procedure, that has improved the efficiency of the procedure *iter* and indirectly the speed in the data collection (ISTAT, 1994). Furthermore, as the Ministero degli Interni (Home Office, 2007) points out, the *mafia* homicides escalation occurred between 1988-1992, with the highest peak in 1991, was contrasted by the State in the following decade, greatly reducing this type of crime. *D98* is included in Model 3 and it is detecting the escalation in bank robberies that occurred in Italy. Finally, *D00* in Model 2 has a negative sign; according to ISTAT (2002) in 2000 a general decrease in certain type of crimes such as homicides is detected as well as a rise in other types of crime, such as sexual assault and extortions.

4.2. The no-Granger Causality null hypothesis

Given two events A and B it is possible to establish whether A precedes B, or B precedes A, or indeed the two events are contemporaneous (Granger, 1988). A standard multivariate Granger causality test is run either augmented with the error-correction term (*ECT*) as derived from the cointegration relationship, or as a VAR when no cointegrating relationship exists amongst the variables. The main findings are provided in Table 6.

The hypothesis that unemployment drives crime is only supported for the thefts case (*LRB*). However, the hypothesis that crime leads to unemployment holds for all crime typologies with the only exception for *LSAK* (robberies, extortions and kidnapping). In the thefts and overall crime models (1 – 6, Table 6) a unidirectional Granger causality runs from either income or output to crime.

Interestingly, the lack of deterrence drives crime against property and overall crime.

5. Conclusions

This paper has analysed crime in Italy for the time span between 1970 up to 2004. The quantitative approach has involved a pre-modelling analysis. To this aim a cointegration and ARDL estimation analysis has been run. A full range of diagnostic statistics has been provided.

This paper has given some answers consistent with the existing literature.

Do socio-economic variables affect crime in Italy? Via a preliminary general-to-specific investigation, it has been possible to parsimoniously reduce the model to a congruent specification. The empirical evidence has shown that socio-demographic variables do not have particular effects on crime activity at a national level. Nevertheless, economic and deterrence variables appear to play a relevant role in explaining crime evolution and patterns. Specifically, the lack of deterrence positively influence the number of thefts, robberies, extortions, & kidnapping, crime against property and total crime.

- Do significant differences emerge when employing different economic variables to analyse crime? In this paper, evidence has been provided that theft and fraud are better explained by per capita real income, while all the other types of crime under investigation are better explained by per capita real production. Hence, in line with the findings of Scorcu and Cellini (1998), particular care should be used in assessing which economic variables best fit crime models.

- Is criminal activity detrimental for legal activity? In this paper evidence has been provided that economic upturns (downturns) can be thought both as a consequence of crime as well as root causes of crime. On the one hand, homicides and crime against property leads to a crowding out effect on real per capita output. On the other hand, all crime typologies (but homicides and fraud) cause a reduction in the employment growth. This outcome is consistent with the trade off between illegal and legal activity from a rational agent perspective.
- Are there specific government acts that influence criminal activity? Given the initial non-normality problems in the residuals, it seems clear that criminal procedure reforms have had an impact on recorded crimes. Specifically, the strongest impact occurred in 1991, one year after the new criminal procedure was introduced. Evidence is given that the gained efficiency in the procedure has indirectly improved the speed in the data collection.

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Table 1 Unit roots test on dependent and explanatory variables (sample: 1970- 2004)

Variable	Determinants - Status	ADF	lags	PP	lags
LRB	c - I(0)	-4.995608 ***	0	-5.039413 ***	3
LH	c,t - **I(1)**	-2.947470	4	-2.858288	4
ΔLH	c,t - I(0)	-3.636170**	4	-8.224444***	11
LSAK	c,t - I(0)	-3.557578*	7	-7.670712***	32
LF	c,t - I(0)	-3.694905**	2	-2.821937	8
LTCP	c,t - **I(1) or I(0)**	-3.133971	8	-4.025393**	3
ΔLTCP	c,t - I(0)	-4.107483**	1	-5.744139***	2
LTC	c,t I(0)	-3.886417**	0	-3.908443**	2
LEM	c,t - **I(1)**	-2.706870	0	-2.402357	7
ΔLEM	c,t - I(0)	-7.889586***	0	-8.530295***	7
LPR	**c,t I(0)**	-4.741978***	8	-6.107679***	4
LURB	c I(0)	-5.359157***	0	-5.540653***	2
LUH	c I(0)	-3.122547**	1	-3.075952**	5
LUSAK	c,t I(0)	-4.070931**	7	-6.754899***	4
LUF	**c I(1)**	-1.197526	0	-1.197526	0
ΔLUF	c,t I(0)	-4.878565***	0	-4.842171***	3
LUTCP	c I(0)	-4.686414***	0	-4.697139***	3
LUTC	c I(0)	-3.673384***	0	-3.576253**	3

Notes: (1) MacKinnon's critical values for rejection of null hypothesis of a unit root. (2) *** and ** indicate statistical significance at the 1% and 5% levels, respectively. (3) Δ denotes the first-difference operator. (4) Number of lags set to the first statistically significant lag, testing downwards; number of lags in the ADF test is set upon AIC criterion and PP test upon Newey-West bandwidth. (5) A constant and trend (c,t) are included upon a trend coefficient statistically significant. (6) All variables are expressed in natural logarithm.

Table 2 Testing Cointegration: an ARDL framework

Equation	k	p	F-statistics				t-statistics	
Model (1)			**Case II**	**Case III**	**Case IV**	**Case V**	**Case III**	**Case v**
LRB=f(LURB, LY, LEM)	3	1	1.84	2.24	-	-	-2.78$^{\vee}$	-
LURB=f(LRB, LY, LEM)	3	2	-	-	4.22*	4.82*	-	-4.11*
ECTLURBLY = LURB -.0093909*LRB -.082819*LY + .088067*LEM + .92165*C + .008576*TREND (-1.54) (-5.01)*** (1.44) (5.76)*** (2.90)**								
LY=f(LRB, LURB, LEMP)	3	3	1.20	1.08	-	-	-0.77	-
LEM=f(LRB, LURB, LY)	3	1	3.29*	3.94*	-	-	-3.03$^{\vee}$	-
Model (2)								
LH=f(LUH, LPR, LEM)	3	2	1.05	1.16	-	-	-1.54	-
LUH=f(LH, LPR, LEM)	3	1	3.35*	3.48 $^{\vee}$	-	-	-3.61*	-
LPR=f(LH, LUH, LEM)	3	2	-	-	2.17	1.88	-	-2.41
LEM=f(LH, LUH, LPR)	3	1	1.78	2.14	-	-	-1.59	-
Model (3)								
LSAK=f(LUSAK, LPR, LEM)	3	1	2.92	2.72	-	-	-2.45	-
LUSAK=f(LSAK, LPR, LEM)	3	1	3.81**	2.15	-	-	-1.12	-
ECTLUSAK = LUSAK -0.28174*LSAK +0.46805*LPR -0.30609*LEM -5.5166*C (-5.15)*** (2.53)** (-0.33) (-1.73)*								
LPR=f(LSAK, LUSAK, LEM)	3	3	0.88	0.58	-	-	-	-0.07
LEM=f(LSAK, LUSAK, LPR)	3	3	2.82$^{\vee}$	2.03	-	-	0.14	-
Model (4)								
LF=f(LUF, LY, LEM)	3	1	-	-	2.03	2.29	-	-2.81
LUF=f(LF, LY, LEM)	3	3	2.77$^{\vee}$	3.45$^{\vee}$	-	-	-0.08	-
LY=f(LF, LUF, LEM)	3	2	1.68	1.82	-	-	-2.22	-
LEM=f(LF, LUF, LY)	3	1	-	-	3.77*	2.78	-	-3.26$^{\vee}$
Model (5)								
LTCP=f(LUTCP, LPR, LEM)	3	2	3.27*	3.77$^{\vee}$	-	-	-3.45$^{\vee}$	-
LUTCP=f(LTCP, LPR, LEM)	3	1	-	-	4.27**	5.33**	-	-4.20**
ECTLUTCP= LUTCP -.059270*LTCP + .034754*LPR -.052176*LEM + 0.001683*TREND (-2.68)** (2.08)** (-1.95)* (-8.51)***								
LPR=f(LTCP, LUTCP, LEM)	3	3	1.43	1.11	-	-	-0.33	-
LEM=f(LTCP, LUTCP, LPR)	3	2	1.16	1.87	-	-	-1.60	-
Model (6)								
LTC=f(LUTC, LPR, LEM)	3	2	2.24	2.33	-	-	-3.23	-
LUTC=f(LTC, LPR, LEM)	3	2	1.08	1.32	-	-	-1.88	-
LPR=f(LTC, LUTC, LEM)	3	1	-	-	8.20***	3.72$^{\vee}$	-	-3.41$^{\vee}$
ECTLPRLTC = LPR -1.0523*LTC + 1.5680*LUTC + 5.1752*LEM -.025136*TREND (-2.65)** (2.40)** (1.56) (1.64)								
LEM=f(LTC, LUTC, LPR)	3	1	3.20$^{\vee}$	2.03	-	-	-2.18	-

Notes: *, **, ***, statistically significant at the 10%, 5% and 1% respectively; when * the null hypothesis of no cointegration holds, as only 33 observations are employed (see Narayan and Smyth, 2004,2006); $^{\vee}$ = inconclusive inference; k= number of regressors included into the equation; p = number of lags; Case II and III with restricted and no restricted constant, respectively; Case IV and V with restricted trend and unrestricted constant, and unrestricted trend and unrestricted constant, respectively. Note that a time trend is included only if its coefficient is statistically significant.

Table 3 ARDL static solution framework (crime as dependent variables)

Models	LRB (1,3,2,3)	DLH (3,2,0,1)	LSAK (3,0,3,0)	LF (3,0,0,0)	LTCP (0,1,0,0)	LTC (0,1,0,0)
C	**32.29 (4.35***)**	-0.62 (-0.91)	**0.33 (2.46**)**	**23.89 (2.28**)**	**46.65 (4.61***)**	**2.49 (2.60**)**
LUNK	**17.35 (2.27**)**	0.006 (0.21)	**3.55 (11.85***)**	-0.28 (-1.33)	**7.31 (5.84***)**	**1.03 (4.63***)**
LY	**-2.78 (-3.33***)**	-	-	**-2.43 (-2.01*)**	**-**	**-**
LPR	-	0.04 (0.94)	**1.35 (5.73***)**	-	**-2.79 (-3.80***)**	**0.43 (6.61***)**
DLEM	**-13.04 (-2.27**)**	**2.69 (4.24***)**	0.53 (0.19)	-0.78 (-0.12)	2.66 (1.65)	-2.15 (-1.63)
Trend	**0.05 (4.08***)**	-	**-**	**0.10 (5.26***)**	**0.09 (4.55***)**	-
D91	**0.81 (3.76***)**	**0.16 (4.96***)**	-	-	-	-
D98	-	-	**0.33 (2.46**)**	-	-	-
D00	-	**-0.15 (-4.14***)**	**-**	-	**-**	**-**
R^2	0.908	0.879	0.994	0.873	0.843	0.834
AR	F(1,15)=0.586	F(1,18)=0.110	F(1,19)=0.308	F(1,22)=0.323	F(1,24)=0.812	F(1,25)=0.367
FF	F(1,15)=1.80	F(1,18)=0.103	F(1,19)=0.694	F(1,22)=1.184	F(1,24)=2.800	F(1,25)=1.146
Norm	χ^2=1.14	χ^2=0.271	χ^2=0.853	χ^2=0.820	χ^2=0.284	χ^2=0.315
Heter	F(1,29)=4.63**	F(1,29)=0.689	F(1,29)=0.327	F(1,29)=7.73**	F(1,29)=0.002	F(1,29)=0.506

Notes: (1) ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. (2) D denotes the first-difference operator. (3) ARDL set upon AIC criterion. (4) Models run in MFit 4.0 (1997). (5) **AR** = serial correlation; **FF**= functional form; **Norm** = normality; **Heter** = heteroschedasticity.; tests from the dynamic specification. (6) ° coefficients of the first statistically significant lag.

Table 4 ARDL dynamic solution; crowding out effect (LPR – LY as dependent variables)

Models	LY (LRB) (1,0,0,0)	LPR (DLH) (1,3,1,0)	LPR (LSAK) (1,2,3,1)	LY (LF) (1,0,0,0)	LPR (LTCP) (1,0,0,1)	LPR (LTC) (0,0,0,1)
C	0.71 (3.31***)	9.77 (4.82***)	7.55 (2.77**)	0.66 (2.60**)	7.12 (3.28***)	0.01 (1.68)
LCRIME°	-0.02 (-0.82)	**-0.06 (-1.92*)**	0.04 (1.23)	0.003 (0.39)	**-0.07 (-2.48**)**	0.03 (1.17)
LUNK°	0.28 (0.84)	-0.06 (-2.29**)	0.12 (1.70)	0.02 (1.36)	0.47 (1.84*)	0.01 (0.20)
DLEM°	1.05 (4.15***)	1.55 (5.07***)	-0.40 (-1.16)	1.03 (4.04***)	-0.74 (-2.17**)	-0.68 (-1.99*)
Trend	-	0.02 (4.34***)	0.01 (2.43**)	**-**	0.01 (3.19***)	-
ECT	-	**-**	-	-	-	**-0.06 (-2.90***)**
D75	-	-	-	-	-	-0.05 (-3.16***)
R^2	0.991	0.998	0.998	0.991	0.997	0.682
AR	F(1,25)=0.015	F(1,20)=0.445	F(1,18)=0.330	F(1,25)=0.064	F(1,23)=0.070	F(1,25)=0.043
FF	F(1,25)=0.451	F(1,20)=4.944**	F(1,18)=2.031	F(1,25)=0.040	F(1,23)=6.44**	F(1,25)=3.573*
Norm	χ^2=3.09	χ^2=0.496	χ^2=1.258	χ^2=3.929	χ^2=0.261	χ^2=0.372
Heter	F(1,29)=0.31	F(1,29)=3.309*	F(1,29)=0.475	F(1,29)=0.237	F(1,29)=1.507	F(1,31)=4.57**

Notes: (1) ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. (2) D denotes the first-difference operator. (3) ARDL set upon AIC criterion. (4) Models run in MFit 4.0 (1997). (5) **AR** = serial correlation; **FF**= functional form; **Norm** = normality; **Heter** = heteroschedasticity.; tests from the dynamic specification. (6) ° coefficients of the first statistically significant lag.

Table 5 ARDL dynamic solution; crowding out effect (*DLEM* as the dependent variable)

Models	DLEM (LRB) (3,3,3,3)	DLEM (DLH) (0,1,3,0)	DLEM (LSAK) (2,2,3,0)	DLEM (LF) (3,3,3,2)	DLEM (LTCP) (1,3,0,3)	DLEM (LTC) (1,3,0,3)
C	1.17 (2.63**)	-4.70 (-5.59***)	-4.38 (-4-45**)	-0.04 (-0.29)	-0.10 (-1.17)	0.03 (0.36)
LCRIME°	**-0.04 (-4.11***)**	**0.04 (3.15***)**	**-0.05 (-3.13***)**	**0.01 (2.91**)**	**-0.04 (-3.17***)**	**-0.05 (-3.77***)**
LUNK°	0.71 (4.22***)	0.02 (1.86*)	0.09 (1.90*)	-0.01 (-1.88*)	0.09 (0.89)	0.05 (2.93***)
LPR - LY°	-0.34 (3.86***)	0.34 (5.56***)	0.32 (4.26***)	-0.13(1.89*)	0.28 (4.24***)	-0.14 (-1.89*)
Trend	0.002 (2.89**)	-0.01 (-5.16***)	-0.01 (-2.45**)	-	-	-
R^2	0.913	0.756	0.777	0.853	0.769	0.840
AR	F(1,13)=0.050	F(1,21)=0.864	F(1,18)=0.189	F(1,15)=3.000	F(1,19)=0.520	F(1,19)=0.060
FF	F(1,13)=1.933	F(1,21)=0.725	F(1,18)=0.787	F(1,15)=3.032	F(1,19)=2.360	F(1,19)=0.600
Norm	χ^2=0.410	χ^2=0.867	χ^2=0.029	χ^2=1.067	χ^2=0.764	χ^2=0.752
Heter	F(1,29)=0.335	F(1,29)=0.026	F(1,29)=0.661	F(1,29)=1.339	F(1,29)=1.679	F(1,29)=0.094

Notes: (1) ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. (2) *D* denotes the first-difference operator. (3) ARDL set upon AIC criterion. (4) Models run in MFit 4.0 (1997). (5) **AR** = serial correlation; **FF**= functional form; **Norm** = normality; **Heter** = heteroschedasticity.; tests from the dynamic specification. (6) ° coefficients of the first statistically significant lag.

Table 6 Temporal Granger Causality

Endogenous variables	F-test				t-test
Model 1	**LRB**	**LURB**	**LY**	**DLEM**	**ECT(-1)**
LRB	-	2.41	**10.89*** **	**7.38** **	-
LURB	2.12	-	1.60	2.52	-1.29
LY	0.27	0.23	-	1.22	-
DLEM	**4.63** **	1.72	**2.77***	-	-
Model 2	**DLH**	**LUH**	**LPR**	**DLEM**	**ECT(-1)**
DLH	-	0.35	0.31	0.31	-
LUH	2.26	-	**7.56***	**7.56** **	-
LPR	0.67	0.76	-	0.56	-
DLEM	**2.71***	0.20	0.62	-	-
Model 3	**LSAK**	**LUSAK**	**LPR**	**DLEM**	**ECT(-1)**
LSAK	-	2.01	1.75	0.12	-
LUSAK	1.00	-	0.57	0.17	-0.38
LPR	0.24	1.14	-	0.48	-
DLEM	1.19	1.02	0.54	-	-
Model 4	**LF**	**DLUF**	**LY**	**DLEM**	**ECT(-1)**
LF	-	0.27	1.66	0.27	-
DLUF	0.26	-	0.73	0.72	-
LY	0.24	0.74	-	0.48	-
DLEM	**4.38** **	1.76	1.66	-	-
Model 6	**LTCP**	**LUTCP**	**LPR**	**DLEM**	**ECT(-1)**
LTCP	-	**2.92***	1.68	0.84	-
LUTCP	0.61	-	0.91	2.74	-1.08
LPR	1.94	**4.12** **	-	**2.51***	-
DLEM	**3.16** **	2.08	0.44	-	-
Model 5	**LTC**	**LUTC**	**LPR**	**DLEM**	**ECT(-1)**
LTC	-	**2.86***	**2.44***	0.86	-
LUTC	0.60	-	0.25	0.28	-
LPR	0.16	0.70	-	0.32	**-2.83*** **
DLEM	**5.19*** **	1.21	0.90	-	-

Notes: *, **, ***, statistically significant at the 10%, 5% and 1% respectively.

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