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Abstract. This paper aims at assessing how offenders allocate their effort amongst several crime typologies. Specifically, complementary and substitution effects are tested amongst number of recorded crimes. Furthermore, the extent to which crime is detrimental for economic growth is also tested. The case study is Italy and the time span under analysis is from 1981:1 up to 2004:4. A Vector Autoregressive Correction Mechanism (VECM) is employed after having assessed the integration and cointegration status of the variables under investigation. The main findings are that a bi-directional complementary effect exists between drug related crimes and receiving, whereas a bi-directional substitution effect is detected between robberies, extortions and kidnapping and homicides and falsity, respectively. Furthermore, economic growth produces a positive effect on the growth of homicides, receiving and drug related crimes; while, the growth in robberies, extortion and kidnapping and falsity have a crowding-out effect on economic growth.

Keywords: Crime; substitution and complementary effect; economic growth; crowding-out effect. **JEL Codes:** K14, C32, E24

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I. Introduction

Since Becker (1968), the standard economic model of crime has primarily been concerned with the criminal's choice between legal and illegal activities. In this framework, the criminal is a rational agent that maximises his/her utility given his/her budget constraint. In the real world, however, the criminal does not have to choose only the optimal allocation of effort between legal or illegal activities, but he/she could allocate his/her effort between several crime offences. A general crime model has to assume that payoffs and sanctions in one crime may affect the level of activity in other crimes. Hence, the relationships between the different "submarkets of crime" (Jantzen, 2008) have to be taken into account in order to explain criminals' behaviour.

In the Nineties, crime economic research has started to focus on the relationship existing amongst different types of crime. For example, Enders and Sandler (1993), within the terrorism economics literature, find that threats and hoaxes are complementary with skyjackings, hostagings and assassinations. Koskela and Virén (1997) show that an increase in punishment or arrest rates makes criminals switch from less to more profitable criminal activities. The present paper, stemming from this strand of research, aims to test for either a complementary or substitution relationship amongst several types of crimes. The crime typologies considered are: number of recorded voluntary committed homicides, robberies, extortions and kidnapping, receiving, falsity and drug related crimes. The analysis is also underpinned by an economics framework by including the real per capita Gross Domestic Product (GDP) as an additional variable. This investigation fits into the current debate testing both the effects that economic growth produces on criminal activity but also highlights possible crowding-out effects running from illegal activity to legal economic activity. Via a Vector Error Correction Mechanism (VECM), it is possible to explore multiple economic correlations both in the short and long run. A set of dummy variables are also included in order to capture the impact of important policy measures such pardons and amnesties on crime rates that took place in Italy during the period under investigation.

To this aim, quarterly Italian data over the period first quarter 1981 – fourth quarter 2004 are employed. Italy can be considered as an interesting case study for several reasons. Firstly, an unprecedented increase in total crime offences has been observed over last 25 years, passing from 39.3 per 1,000 inhabitants in the year 1979 to 50.7 in 2004 (+35.7%). If the time span from 1993 up to 2007 is considered, the number of total crime offences increased by 29.8%, in contrast with many Western countries, such as USA (-20.4%), Canada (-15.8%), the UK (-10.9%), France (-7.5%) and Germany (-6.9%) (Eurostat, 2009). From this point of view, this study makes an important contribution to explore the causes of this large increase by considering the relationship between the different types of crime, and between crime and economic growth.

Secondly, the Italian crime pattern is characterized by a prevalence of property crimes (73.4% of total crime offences) which are better explained by economic motivations. The total thefts account for the 53.8% of the total crimes in Italy (2001), well above, for example, what is observed in the UK, 41.49% (Bolton, 2001), that is one of the countries with the highest crime rate in Europe (Eurostat, 2009). Furthermore, certain types of crime, such as robbery, extortion, receiving, falsity, are committed mostly by organized crime gangs. Hence, this study allows one to investigate the allocation of the organized crime criminal effort.

A promising field of research has developed around the estimation of the social cost of crime. It is well known that crime generates significant negative externalities, causing, tangible and intangible, direct and indirect costs for the community. A recent paper by Detotto and Vannini (2009) gauges the social cost of crime in Italy by analysing a subset of offences, such as street crimes, robbery, fraud and homicide. Their findings show that in the year 2006, the estimated total social cost was about € 40 billions, that represented 2.6% of Italian GDP. It is evident that in Italy the criminal activity has a significant impact on legal activities, and its estimate has important policy implications.

The rest of this paper is organised as follows. Section 2 presents a literature review on crime economics related to time series analysis. Section 3 describes the economic model adopted and the data used. Section 4 explains the methodology and the results are presented. Section 5 gives an account on the findings from the Granger causality test. The last section presents the main conclusions of this study.

II. Literature review

This section is aimed at giving an account on crime economic literature related to the time series analysis. Masih and Masih (1996) estimate the relationship between different crime types and their socioeconomic determinants within a multivariate cointegrated system for the Australian case (1960-1993). Within a Granger test framework, the authors establish the direction of the temporal causation between the variables showing the criminal activity positively responds to urbanization and bad economic conditions, but they fail to find a crime impact on the socioeconomic variables under study.

Using an Australian dataset (1964-2001), Narayan and Smyth (2004), within an ARDL model, examine the relationship amongst unemployment, real wage and seven different crime categories that are homicide, motor vehicle theft, fraud, break and enter, robbery, stealing, serious assault. 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 (2009), applying an ARDL model to the Malaysian case (1973-2003), analyse the relationship between real gross national product and different crime offences. The results indicate that, in all cases, the long run causal effect runs from economic variables to crime rates and not vice versa.

Chen (2009) implements a VAR model to examine the long-run and causal relationships among unemployment, income and crime in Taiwan (1976-2005). The results indicate the presence of long-run relationships amongst unemployment, income and theft and amongst unemployment, income and economic fraud. Moreover, Chen shows the presence of a long-run level equilibrium relationship among unemployment, income and total crime. The Granger causality tests depict a neutral relationship among unemployment, income and all crime categories used

A common theme in the aforementioned studies is the investigation of crime in the context of separate and independent submarkets. They specify a different econometric model for each type of crime without considering possible relationships that may exist amongst various illegal activities. First attempts at closing this gap can be seen with the use of cross-section techniques (Holtmann and Yap, 1978; Hakim et al., 1984; Cameron, 1987). In general, these studies find the presence of positive cross effect of imprisonment and arrest rates among several property crimes. Koskela and Virén (1997), for example, propose a theoretical choice model of crime switching that analyses the occupational behaviour of a representative rational agent between one legal and two criminal activities. These authors test the model within a cointegration and error correction framework using annual data from Finland for robberies and vehicle thefts for the time spam between 1951 and 1992. The findings show the presence of substitution between the two types of crime: namely, an increase in punishment or arrest rates makes criminals switch from less to more profitable activities.

Jantzen (2008) employs a Johansen's cointegration method to estimate the long run equilibrium relationship existing between several crime types, namely murder, assault, robbery, burglary, larceny and vehicle theft. Augmented Granger causality tests are also conducted to identify the direction of causality between the variables. The results indicate the existence of a long run equilibrium relationship between property crimes. Besides, they are Granger caused by violent crimes such as murder and assault.

An interesting case study relates to the analysis of the substitution effect stemming from the economics of terrorism. By implementing a VAR model, Enders and Sandler (1993) study the behaviour of rational terrorists to measure the relationships between various terrorism attack modes, namely skyjackings, incidents involving a hostage, assassinations, threats and hoaxes and all other incident types. A set of dummy variables are included in order to capture the effect of exogenous policy interventions, such as the installation of metal detectors in airports or the retaliatory raid on Libya. The authors find that threats and hoaxes events are complementary with skyjackings, hostagings and assassinations. Moreover, they show the impact effects of policy intervention on each terrorism series.

From this literature review it emerges that the relationship between crime and economic variables, such as GDP and unemployment, has been extensively studied, especially within a time series framework. On the whole, ARDL models have been employed given the use of low frequency data due to the availability of relatively short-span dataset. Furthermore, a great focus on the investigation of the temporal relationship between legal and illegal activity has been given via the standard Granger causality test. Overall, the rather mixed evidence emerges on the type of temporal causality existing between the analysed variables, depending on the econometric approach and country analysed.

However, scarce attention has been given to the investigation on what extent offenders, regarded as rational individuals, allocate their efforts between legal and illegal activities, as well as amongst different types of crimes. To date, only a few studies exist on these specific economic issues. The present study, stemming from this latter strand of research, as provided in the literature review, can be regarded as novel. Possible substitution and complementary effects amongst several types of offences will be investigated within a multivariate framework and a quarterly frequency.

III. Data description

In this paper six crime typologies are employed: number of recorded attempted or committed intentional homicides (*H*), number of recorded robberies, extortions and kidnapping (*R*), the number of receiving - or dealings with stolen property (e.g. archaeological goods) - (*RE*), number of recorded falsity - such as fraud using altered or false documentation - (*F*), and finally the number of recorded drug crimes (*DR*); all these variables are defined per 100 thousands inhabitants. Table 1 provides detailed definitions of the crime variables used in this study. As a further variable, the per capita real GDP is also employed. Quarterly Italian data from ISTAT (*Italian National Institute of Statistics*) over the time span 1981:1 up to 2004:4 are collected.

The empirical analysis has a twofold aim: firstly, to assess for either a substitution or complementary relationship amongst the different crime typologies and, secondly, to pick up possible crowding-out effects between crime and economic growth. The variables under study have been transformed into a natural logarithmic specification (*L*), assuming the existence of a non-linear relationship. A graphical representation of the moving trend proposed by Hodrick and Prescott (calculated using Eviews 4.0) helps identifying the general trend of each series, as shown in Figure 1. An upwards trend characterises receiving (*LRE*) and falsity (*LF*), though the latter shows a reverse pattern at the end of the Nineties. *LR* and *LDR* depict an upwards trend until the beginnings of the Nineties and thereafter show a more stable path of growth. Finally, homicides are characterised by a cyclical pattern with a peak reached in the second half of the Eighties and a recrudescent of this crime occurred in the year 2000.

IV. VECM and empirical results

The function under investigation is the following:

$$LGDP = f\,(LH, LR, LRE, LF, LDR) \qquad (1)$$

where *LGDP, LH, LR, LRE, LF* and *LDR* are the afore mentioned variables. The multivariate system is mathematically defined as follows:

$$\begin{bmatrix} LGDP_t \\ LH_t \\ LR_t \\ LRE_t \\ LF_t \\ LDR_t \end{bmatrix} = \begin{bmatrix} A_{10} \\ A_{20} \\ \dots \\ A_{60} \end{bmatrix} + \begin{bmatrix} A^1_{11} & A^1_{12} & \dots & A^1_{16} \\ A^1_{21} & A^1_{22} & \dots & A^1_{26} \\ \dots & \dots & \dots & \dots \\ A^1_{61} & A^1_{62} & \dots & A^1_{66} \end{bmatrix} \begin{bmatrix} LGDP_{t-1} \\ LH_{t-1} \\ \dots \\ LDR_{t-1} \end{bmatrix} + \dots\dots + \begin{bmatrix} A^k_{11} & A^k_{12} & \dots & A^k_{16} \\ A^k_{21} & A^k_{22} & \dots & A^k_{26} \\ \dots & \dots & \dots & \dots \\ A^k_{61} & A^k_{62} & \dots & A^k_{66} \end{bmatrix} \begin{bmatrix} LGDP_{t-k} \\ LH_{t-k} \\ \dots \\ LDR_{t-k} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \dots \\ \varepsilon_{6t} \end{bmatrix} \qquad (2)$$

where $[A^1]$,… and $[A^k]$ are the p×p (or 6×6) matrices of parameters to be estimated; *k* is the number of lags be considered in the VAR; ε_t is the 1×6 vector of the disturbance terms that are assumed to be uncorrelated with their own lagged values and uncorrelated with all of the right hand side variables.

The methodological framework employed to investigate the relationship amongst these variables consists of three steps. The first step is to test the order of integration. Table 2 gives the results of the augmented Dickey-Fuller (ADF), the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) and Phillips-Perron (PP) test statistics. These tests are used to detect the presence of a unit root for the individual time series and their first differences. Overall, all the test statistics are congruent and indicate that the series are integrated of order I(1) in the level form but I(0) in their first differences (e.g. Engle and Granger 1987). Nevertheless, there is some discrepancy regarding the order of integration for *LR*. Application of the ADF test yields the unit root is rejected when applied to its first difference but there is no evidence when the test is applied to its level. KPSS suggests the series is I(1). Hence, overall there is ground to treat *LR* as stationary in its first difference.

Given the unit root results, the second step is to use the Vector Autoregressive (VAR) approach that Johansen (1988) and Johansen and Juselius (1990) implemented to investigate the existence of a common long run equilibrium amongst I(1) variables. The joint *F*-test and the Akaike (AIC), Schwartz (SC) and Hannan-Quinn (HQ) Information Criteria are used to select the number of lags required in the unrestricted VAR to ensure that residuals are white-noise (*i.e.* the vector autocorrelation test in this case is F(180,197)=1.0352 [0.4054]). Thus, the chosen lag length is four accordingly (Garratt *et al.*, 2003). The cointegration test results are presented in Table 3. Though, the null hypothesis of no cointegration fails to be rejected by the maximum likelihood (Max) statistic, at least a single significant cointegrating vector is identified using the trace statistic. Hence, one concludes that all variables are cointegrated, and causally related in each model. The calculated cointegrating vector (*ECT*), that is the residual from the long run equation, is then incorporated in its first lag in the error correction specification.

The third step of the analysis is to estimate an unrestricted vector error correction model (VECM) where the long run and short run information are simultaneously included:

$$DY_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i Y_{t-i} + \mathrm{K} DM_t + \varepsilon_t \qquad (3)$$

where: *Yt = (LGDPt, …. ,LDRt)* is a vector of all the endogenous variables defined above, expressed in their first difference (*D*) being I(1); Π is the long run part of the model, that contains the cointegrating relations (β) and the loading coefficients (α); Γ is the matrix of the short run parameters to be estimated; *DM* contains all deterministic variables that is constants, linear trend and specified other dummy variables; ε_t is the vector of the disturbance terms that are assumed to be uncorrelated with their own lagged values and uncorrelated with all of the right hand side variables. Specifically, the deterministic components of the system are the following: a linear trend included based on the vector joint *F*-test (4.61953 [0.001]); a set of 0-1 dummy variables (*d83q3, d85q3, d85q4, d86q1, d89q4, d91q1, d96q4, d00q1 and d03q4)* that pick up possible leap and lag effects caused by specific government acts (e.g. amnesties, pardons, de-penalisations, structural reforms) as well as to avoid problems of non-normality in the diagnostics. The advantage of a VECM model consists of it being an a-theoretic simultaneous system that allows one to include all the crime and economic variables endogenously.

The vector diagnostics of the unrestricted VECM are reported in Table 4. A problem of non-normality is still present at the 5% level; however, the inclusion of further deterministic dummy variables further worsens the estimation. Overall, the model is a congruent specification and the best system achievable. Hence, a general-to-specific simplification is used to reduce the system to an efficient and congruent encompassing specification (see Mizon, 1996; Hendry and Mizon, 1998 for detailed methodological issues). The final parsimonious models are reported in Table 5. The coefficient restriction is based on the 10% level of significance threshold. The likelihood-ratio test of the over-identifying restrictions is $Chi^2(117) = 68.753[0.9999]$, hence the null hypothesis fails to be rejected.

DLGDP and *DLDR* are the best estimated models in terms of diagnostic statistics. The equations for *DLH* and *DLRE* show problems of autocorrelation, though at the 5% level and the equations for *DLR* and *DLF* depict non-normality problems. However, inefficiency issues are not uncommon in core macroeconometric models (e.g. Garratt *et al.*, 2003).

In terms of long run equilibrium, the ECT_{t-1} turns out to be statistically significant in all the equations with the only exception for the receiving crime equation (*DLRE*), where only short run dynamics can be accounted for. Besides, in four of the models the sign is negative that implies the variables tend to converge to a common equilibrium. The fastest convergence is experimented in the *DLDR* equation.

The short run dynamics give insightful information on the relationships existing amongst the variables under investigation. Table 6 provides a summary of the main findings. The first equation *DLH* (homicides) denotes complementary effects with falsity and drug crimes, whereas there is a substitution effect between homicides and robberies, extortions and kidnapping (*DLR*). The first outcome can be explained by the fact that drug related crimes can be a cause of homicides. The second outcome is also reasonable since those who commit robberies, extortions and kidnappings are most likely to consider victims as an asset and it is in their own interest to keep them alive. Besides, robberies, extortions and kidnapping are important sources of funds for organised crime groups, while homicides are often instruments of control of the territory, not uncommon for example in the South of Italy. Thus, there seems to be a trade off between the activity of fund raising and territory occupation.

From the second equation (*DLR*), a substitution effect arises between robberies, extortions and kidnapping, and homicides, receiving and falsity, respectively; however, a complementary effect is detected between *DLR* and drug related crimes.

The third equation (*DLRE*) highlights a unique complementary effect between receiving and drug related crimes. Complementary effects of drug related crimes in the second and third equation can be explained by the fact that drug offenders are more likely to commit crimes, such as robberies and receiving, in order to fund a drug habit.

The fourth equation (*DLF*) results show a substitution effect between falsity and robberies, extortions and kidnapping (*DLR*), and drug related crime (*DLDR*), respectively. In addition, a complementary effect exists between falsity and receiving.

From the drug related crime equation (*DLDR*), a substitution effect emerges for homicides and a complementary effect for receiving. The former outcome can be easily justified with the fact that homicides are most unlikely to cause drug related crime; nevertheless, the opposite causality has been established in the first equation.

As a further step of the analysis, the relationship between crime categories and economic growth has been analysed. Overall, economic growth has a positive impact on the growth of homicides, receiving and drug related crime, whereas an increase in the economic growth will cause a reduction in the growth of robberies, extortions and kidnapping (*DLR*) (see last column in Table 6).

The reverse relationship is examined in the last equation (*DLGDP*). A crowding-out effect on the economic growth is detected for robberies, extortions and kidnapping (*DLR*) and falsity (*DLF*); whereas, an increase in the growth of homicides (*DLH*) and receiving (*DLRE*) have a positive effect on economic growth. The connection between homicides and economic growth is statistically significant although the causal relationship not clear (see Table 6). It is worth highlighting that Italy is a special case due to the presence of organised criminal gangs (Mafia, Camorra, etc); mafia groups use murders as a means to gain power, hence it is reasonable to believe that homicides rate increases as their illicit activities grow up along with GDP growth. In this regard, the Association of the Confederation of Commercial Activities (Confesercenti, 2008) estimates the total revenue of organised crime accounts for 130 billion euros, that is 9% of Italian GDP. The latter outcome is consistent with the possibility that receiving can produce multiplier effects in the Italian legal economic system.

V. Conclusions

This paper has aimed to expand existing economic crime literature, by employing a more robust VECM analysis thanks to the use of quarterly data (1981:1-2004:4). Italy makes an interesting case study for the high frequency of organised crime and economic motivated crime, such as receiving, falsity, property crimes and so on. In this sense, we expect to find a rational behaviour among crime agents. The objective of this study has been firstly to examine how criminals allocate their effort amongst different crime typologies, secondly to what extent crime affects economic growth, as well as economic growth affects criminal activity.

The pre-modelling results have shown that a long run unique common equilibrium exists amongst the criminal variables (i.e. number of recorded homicides; robberies, extortions and kidnapping; receiving; falsity; and drug related crimes) and GDP. On this basis, the VECM model has highlighted the following findings: firstly, economic growth produces a positive effect on the growth of homicides, receiving and drug related crimes, conversely, a negative effect on robberies, extortions and kidnapping; secondly, the growth in robberies, extortions and kidnapping and falsity has a crowding-out effect on economic growth, while homicides and receiving produce a positive effect on legal activities.

The VECM has also shown how offenders allocate their effort amongst the crime typologies analysed. Specifically, with regard to the short run dynamics, a bi-directional complementary effect has been detected between drug related crimes and receiving. Whereas, a bi-directional trade off effect has been highlighted between robberies, extortions and kidnapping, and homicides and falsity, respectively.

Further findings have shown that growth in drug related crimes increase growth in homicides but a trade off effect has also been highlighted when treating homicides as the dependent variable.

Although, Italian data have been employed in this study, the findings should be of interest and replicated for other countries. Economic issues, such as crowding-out effects of illegal activity and offenders' allocation of their effort in criminal submarkets, have been so far under-researched despite its substantial importance to government interventions. This paper helps to shed new light on these topics.

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Figure 1 Graphs of *LH*, *LR*, *LRE, LF, LDR, LGDP* and Hodrick-Prescott trend

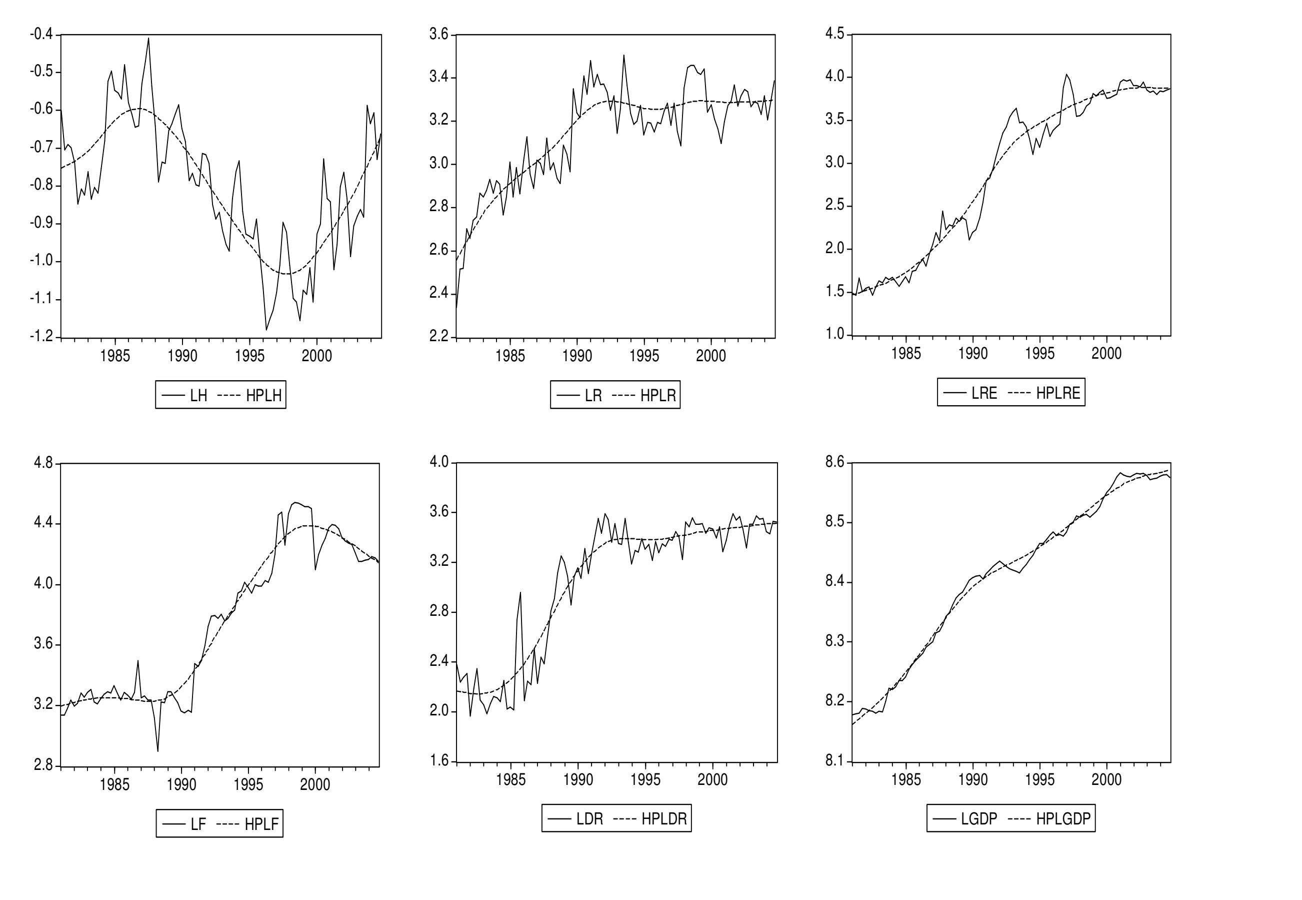

Table 1 List of crime variables (Number of recorder crimes per 100,000 inhabitants)

Name	**Definition**	**Code**
Homicide	Voluntary committed homicide	H
Robberies, extortions and kidnapping	Robberies, extortions and kidnapping	R
Receiving	A receiving offence is committed when a person who intentionally handles, receives, retains or disposes of stolen goods, knowing or having reasonable grounds to believe they have been stolen	RE
Falsity	A falsity offence regards counterfeit of credit cards and currency, false seals (*e.g.* brand counterfeit, falsification of stamps or passports of the State) and falsifying documents (*e.g.* alteration of official documents and certificates)	F
Drug	Offence of possession, production and trade of drugs	DR

Table 2 Unit roots test on dependent and explanatory variables (sample: 1981:1- 2004:4)

Variables	Status	ADF	lags	KPSS	lags	PP	Lags
LGDP	c,t - I(1)	-1.96	4	0.23***	7	-1.68	5
DLGDP	c,t - I(0)	-4.39***	3	0.07	5	-6.72***	4
LH	c - I(1)	-1.34	7	0.63**	7	-2.29	11
DLH	c - I(0)	-4.38***	7	0.20	22	-10.26***	24
LR	c,t - I(0) or I(1)	-3.05**	2	0.26***	6	-3.88**	4
DLR	c - I(0)	-9.82***	1	0.19	2	-14.40	2
LRE	c,t - I(1)	-1.07	6	0.20**	7	-1.05	3
DLRE	c - I(0)	-3.66***	5	0.11	3	-9.88***	3
LF	c - I(1)	-1.13	0	1.15**	7	-1.06	2
DLF	c - I(0)	-10.90***	0	0.11	2	-10.90***	1
LDR	c,t - I(1)	-1.12	3	0.25***	7	-2.77	3
DLDR	c - I(0)	-8.33***	2	0.23	49	-15.58***	27

Notes: (1) *** and ** indicate statistical significance at the 1% and 5% levels, respectively. (2) *D* denotes the first-difference operator. (3) Number of lags set in the ADF test is set upon AIC criterion, whereas KPSS and PP test upon Newey-West bandwidth. (4) A constant and trend (c,t) are included upon a trend coefficient statistically significant.

Table 3 Johansen cointegration trace test

***Lgdp lh lr lre lf ldr* - Sample: 1981:1 – 2004:4 - 4 lags - constant**						
H0:rank<=	**Trace**	**95%**	**99%**	**Max**	**95%**	**99%**
0	**111.61*** **	94.15	103.18	38.47	39.37	45.1
1	73.14**	68.52	76.07	29.55	33.46	38.77
2	43.59	47.21	54.46	15.77	27.07	32.24
3	27.81	29.68	35.65	15.09	20.97	25.52
4	12.72	15.41	20.04	8.09	14.07	18.63
5	4.63**	3.76	6.65	4.63**	3.76	6.65

Notes: (1) **, *** denote that a test statistics at the 5% and 1 % levels of significance, respectively. (2) four lags and an unrestricted constant are added; equivalent results are obtained when including both the constant and the trend in the cointegrating space.

Table 4 Unrectricted VECM, vector diagnostic statistics

tests	**distribution**	**statistics**	**p-value**
Vector autocorrelation	F(180, 126)	0.96841	0.5812
Vector Normality	Chi^2(12)	25.005**	0.0148
Vector heteroscedasticity	Chi^2(12)	1225.1	0.8661

Notes: (1) ** indicate significance at the 5% level

Table 5 VECM – parsimonious specification

Variables	Models					
	DLGDP	DLH	DLR	DLRE	DLF	DLDR
DLGDPt-1	0.392 (0.092)***	-	-4.893 (1.754)***	-	-	-
DLGDPt-2	-	-	3.645 (1.838)*	3.646 (1.838)*	-	-
DLGDPt-3	0.268 (0.095)***	2.423 (1.21)**	-3.124 (1.846)*	-3.124 (1.846)*	-	5.131 (2.240)**
DLGDPt-4	-	-	4.653 (1.770)**	4.653 (1.770)**	-	
DLHt-1	0.012 (0.006)**	0.200 (0.075)**	-0.281 (0.095)***	-	-	-0.401 (0.143)***
DLHt-2	0.011 (0.006)*	0.167 (0.074)**	-	-	-	-
DLHt-3	-	-0.474 (0.074)***	0.241 (0.092)**	-	-	-
DLHt-4	-	-	-	-	-	-
DLRt-1	-	-	-0.218 (0.081)**	-	-	-
DLRt-2	--	-	-0.269 (0.079)***	-	-0.273 (0.076)***	-
DLRt-3	-0.008 (0.005)*	-0.106 (0.060)*	-	-	-	-
DLRt-4	-	-	-	-	-0.259 (0.071)***	-
DLREt-1	-	-	-	-	0.149 (0.073)**	-
DLREt-2	-	-	-	0.183 (0.089)**	-0.160 (0.072)**	-
DLREt-3	-	-	-0.173 (0.063)***	-	-	-
DLREt-4	0.009 (0.004)**	-		-	-	0.303 (0.102)***
DLFt-1	-	-	-0.154 (0.075)**	-	-	-
DLFt-2	-	0.100 (0.061)*	-	-	-	0.259 (0.071)***
DLFt-3	-0.013 (0.005)***	-	-	-	-	-
DLFt-4	-		-	-	-	-
DLDRt-1	-	0.091 (0.035)**	-	-	-	-0.253 (0.067)***
DLDRt-2	-	-	0.119 (0.044)***	0.170 (0.059)***	-	-
DLDRt-3	-	-		-	-0.125 (0.048)**	-0.143 (0.065)**
DLDRt-4		0.079 (0.035)**	-0.080 (0.043)*	-	0.185 (0.045)***	-
Cit-1	-0.006 (0.002)***	-0.128 (0.030)***	0.154 (0.037)***	-	-0.074 (0.032)**	-0.141 (0.056)**
Trend	0.000 (0.000)**	0.004 (0.001)***	-0.006 (0.001)***	-	0.002 (0.001)**	0.005 (0.002)**
d83q3	0.018 (0.005)***	-	-	-	-0.191 (0.069)***	-
d85q3	-	-	-	-	-	0.702 (0.100)***
d85q4	-	-	-0.184 (0.071)**	-	-	0.387 (0.115)***
d86q1	-	-	-	-	-	-0.752 (0.112)**
d89q4	-	0.169 (0.060)***	0.308 (0.073)***	-0.235 (0.088)**	-	-
d91q1	0.009 (0.005)*	-	0.162 (0.070)**		0.262 (0.070)***	-
d96q4	-	-	-	0.403 (0.089)***	-	-
d00q1	-	0.186 (0.057)***	-	-	-0.398 (0.072)***	-
d03q4	-	0.349 (0.053)***	-	-	-	-
Constant	0.003 (0.001)**	-	0.048 (0.023)**	0.047 (0.026)*	0.047 (0.021)**	-
Sigma	0.005	0.057	0.072	0.086	0.073	0.110
AR F(5,50)	2.234	2.416**	2.201	2.534**	2.173	2.279
Nor Chi^2(2)	1.658	0.946	7.429**	0.290	16.965***	0.685
CHeter F(4,67)	0.877	0.884	1.010	1.404	0.858	0.263
Heter Chi^2(61)	66.605	52.417	47.364	58.769	69.436	50.458

Notes Table 5: (1) ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. (2) *D* denotes the first-difference operator. (3) Parsimonious VECM set upon joint F-test on coefficient restriction and information criteria. (4) Models run in Givewin 2.00 (2001). (5) **AR** = serial correlation; **Norm** = normality; **CHeter**= conditional heteroscedasticity; **Heter** = heteroscedasticity. (5) Standard errors in parenthesis.

Table 6 Substitution/complementary effects and crowding-out effects on economic growth

	Effects based upon the first significant lag at least at the 10%					
Variables	**DLH**	**DLR**	**DLRE**	**DLF**	**DLDR**	**DLGDP**
DLH	-	S*		C*	C**	Pos**
DLR	S***	-	S***	S**	C***	Neg***
DLRE			-		C***	Pos*
DLF		S***	C**	-	S**	
DLDR	S***		C***		-	Pos**
DLGDP	Pos**	Neg*	Pos**	Neg***		-

Notes: Effects based upon the first significant lag at least at the 10% (see Pindyck, and Rubinfeld, 1991); related coefficients statistically significant at the 10% (*), 5%(**) and 1%(***) respectively.