Development, Crime, and Punishment: Accounting for the International Differences in Crime Rates[*]

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Abstract

This paper explores the relation between development and crime. The previous literature has consistently found positive links between crime and development. This paper demonstrates that these earlier results are due not to increases in crime with development, but rather to increases in crime report. It uses two cross sections, one based on victim survey data and the other on official data, to arrive at this conclusion. The results of the analysis of a panel of official data corrected for the "reporting bias" suggest that development, if anything, affects crimes negatively. Income inequality is found to be the variable most closely related to crime rates (positively).

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1 Introduction

Crime rates di®er enormously among countries, and their variation in this dimension is orders of magnitude greater than their variation through time in a given country. For example, the number of homicides per 100,000 inhabitants, probably the most popular crime statistic, was around 17.2 and 9.6 in 1994 for, respectively, Mexico and U.S., while at the same year it was close to 1.2 and 0.6 for Sweden and Japan, respectively. And the same U.S., after sustaining an impressive and consistent decline in this statistic in the 7 years following 1990, reduced it by only 25% of its initial value. Part of these di®erences among countries are due to distinct de¯nitions of crimes and to di®erent reporting rates, but it seems obvious that structural { or at least slowly changing { characteristics of the countries should also play a role in determining di®erences as these ones. Natural candidates are, among others, cultural traditions, religion, and economic development. The goal of this paper is to explore the role played by di®erent dimensions of economic development in explaining the cross-country di®erences in crime rates.

Criminologists for a long time have been interested in the relationship between crime rates and economic development. Nevertheless, the view that "the primary concern of applied criminology should be to study crime within a speci¯c category and location" (Burnham, 1990, p.44) made di±cult the development of an uni¯ed body of theoretical work and comparable empirical evidence[1].

The economic theory of crime, on the other hand, o®ers a set up where crimes that seek income, or that are by-products of income seeking activities, become "part of a much more general theory and do not require ad hoc concepts" to be explained (Becker, 1968, p.176). As in any other economic theory, costs and bene¯ts guide the choice: a person commits a crime if the gain associated with it exceeds the opportunity cost of the alternative use of resources. Although a considerable part of the crimes committed are not included in this category (mainly sexual, hate, and part of the so called violent crimes), we believe that most of the quantitative di®erences in international crime rates is due to "economic" crimes, and, besides, that these crimes are the ones most sensible to policy measures and to changes in

[1]For some reason, it also seems to be a common belief that criminal justice institutions and the law are more important factors in determining crime rates than socio-economic variables (Burnham, 1990).

economic conditions. In Stigler's (1970, p.530) words, "(this kind of criminal) seeks income, and for him the usual rules of occupational choice will hold".

What makes this particular "occupation" so special is the fact that, apart from the people employed in it, the whole society sees it as an undesirable and harmful activity, and is usually willing to spend a positive amount of resources to reduce its incidence. Besides that, some of the variables that the economic theory predicts to be fundamental in determining the attractiveness of this "occupation" are variables intimately related to the transformations that a country goes through in the di®erent stages of economic development (changes in income distribution, urbanization, income per capita, etc.). Thus, the link between development and crime rates seems to call naturally for an economic interpretation, and this may in part be the reason why criminology has not yet come to an agreement on this issue.

This paper analyzes how the changes usually associated with economic development a®ect crime rates. In trying to assess this question, we face the traditional problem of underreporting present in the international data sets based on o±cial records. To overcome it, we use a new cross-section of international victim survey data , what allows us to study the characteristics of the reporting error and to suggest an econometric approach to overcome the bias that it may induce.

The results suggest that the positive link between crime and development usually cited in the criminology literature does not exist. Reporting rates of crimes are strongly related to development, mainly to income per capita, what points out that the conclusion that development is criminogenic was basically a consequence of the correlation between the reporting error and the development related variables. The results of the panel data estimation with the corrected panel data indicate that income inequality a®ects crime rates positively and economic development, if anything, a®ects it negatively, although short run increases in income may increase certain types of crimes. Additional evidence from a larger panel of o±cial homicide data, supposedly not so seriously contaminated by the measurement problem, generally supports these conclusions.

The paper begins with a discussion of the links between economic development and crime predicted by the economic theory of crime (section 2). Section 3 presents the existing empirical evidence linking crime and development and discusses its problems. Section 4 describes the two data sets used here { one panel based on o±cial records and one cross-section based on a victim survey – and uses it to illustrate and analyze the bias induced by the official data. An alternative approach, that tries to correct the bias existent in the official data and to allow the use of the panel, is proposed, applied, and evaluated in section 5. The last section discusses the conclusions of the paper.

2 Economic Development and The Economics of Crime

The potential relation between different dimensions of development and crime rates is already clear in the classic work of Ehrlich (1973). Ehrlich was the first to construct an explicit model of participation on illegitimate activities, where individuals decide on the allocation of their time among non-market, legal, and illegal activities. The model predicts effects of income distribution (positive), wealth (not determined), and probability of apprehension (negative) on the crime rates.

From these factors, inequality is the one that received most attention from economists. Recently, Chiu and Madden (1998) developed this idea in detail in analyzing the determinants of burglary rates, and Bourguignon (1999) used it to show the sizeable economic costs that inequitable economic development may generate.

The probability of apprehension, on the other hand, is more directly determined by the degree of law enforcement and number of policemen per capita, but it is also related to a variable that suffers significative changes throughout a country's development process: the degree of urbanization. Glaeser and Sacerdote (1996), for example, discuss this aspect of the link between urbanization and incidence of crime, together with other reasons why we should expect an effect of population density on crime rates (higher pecuniary return to crimes, social influences, and development of tastes).

The average income, probably the variable most commonly identified as economic development itself, did not receive nearly so much attention. This is probably due to the fact that the standard economic model – in the Ehrlich's line – despite predicting that average income may have an effect on crime rates, does not determine which will be the sign of this effect, which depends primarily on how risk aversion changes with income, and it seems that economists are not willing to make a generalization in this direction in order to be able to sign it. Indeed, it does not even sound very intuitively appealing the idea that the basic relation between income level and crime rates would be through changes in the degree of risk aversion.

Finally, other variables related to development may also have some indirect (non-economic) e®ects on the incidence of crime. Education and institutional development, for example, may shift preferences (moral standards and values) in some way not clearly predicted by the economic theory. We will try to control for these factors in the empirical analysis, but we concentrate our attention basically on the roles played by income level, distribution, and urbanization, with less emphasis in the later, given the natural appeal that the ¯rst two variables have to economists.

So, to a great extent, the e®ect of some basic economic variables on crime rates is theoretically indeterminate, and the question becomes fundamentally an empirical one. In this respect, the vast majority of empirical studies available was not done by economists, and altogether they are far from arriving at a consensus in terms of the e®ects of the di®erent variables on crime levels. The next section presents a quick review of the existing empirical literature.

3 Previous Evidence

The empirical evidence on the determinants of cross-regional di®erences in crime rates is mainly concentrated on the e®ects of development (income level or some measure of poverty) and inequality, and there is basically no continued and systematic debate regarding the e®ects of other social-economic variables (as urbanization or education, for example). As our primary interest here is also related to these two variables, we are going to center this quick review of the literature and much of the subsequent discussion on them (reviews of the criminology literature are also presented in Patterson, 1991 and Fowles and Merva, 1996).

Tables 1 and 2 summarize the results of several studies that tried to analyze the e®ects of, respectively, inequality and development on crime rates. These tables do not intend to be comprehensive reviews of all the evidence available, nor detailed descriptions of the techniques and strategies adopted in the various papers. Instead, their goal is to give a broad view of the general results obtained and of how criminologists themselves see the present stage of this debate (in this direction, see Patterson, 1991 or Fowles and Merva, 1996). The statistical approaches used in the di®erent studies are as diverse as they could possibly be, and so we decided simply to report the units and dimension of analysis, the types of crimes analyzed, and the ¯nal conclusion as the authors themselves present it (or as their numbers would suggest in a super¯cial look). For the inequality case, 11 studies used cross-sections, 2 used panel data, and 2 used time series; 13 used U.S. data (neighborhoods, cities, SMSA's, counties, or national data), and only 2 used international data; the Gini coe±cient was the choice of inequality measure in virtually all the cases (13). In the development studies, 16 cases used cross sections, 5 used panel data, and 1 used time series; 15 used U.S. data (neighborhoods, cities, SMSA's, counties, or national data) and 7 used international data; the measure of development was income per capita in 4 cases, incidence of poverty (according to some income level or poverty line) in 15 cases, and other measures (energy consumption, diversi¯cation of industry, etc.) in the rest. Speci¯c details are presented in Tables 1 and 2.

The major part of the evidence regards within United States studies, with the units varying from neighborhoods and cities to counties and metropolitan areas. As can be seen from Table 1, the results on inequality in this case vary between positive and non-signi¯cant from crime to crime and from study to study, leaving no clearly identi¯able pattern. In relation to development, Table 2 shows that the U.S. studies most often indicate a negative e®ect of income level (or positive e®ect of poverty level) on crime rates, although non-signi¯cant and even positive results are present. Despite this fact, it seems fair to say that the U.S. evidence generally suggests a negative e®ect of income levels on crime rates and, not very convincingly, a positive e®ect of inequality.

The international evidence, surprisingly, suggests a conclusion strikingly di®erent from this one. While the few inequality studies, as in the U.S. case, leave no clear answer, the evidence on development seems to be overwhelming: virtually all the international evidence suggests that development and crime rates are positively and signi¯cantly correlated. The only consistent exception in all cases is homicide/murder rates; all other types of crimes are positively related to the income level in all seven studies presented in Table 2. This is certainly the most consistent of all the possible results that can be read from Tables 1 and 2.

Although maybe surprising for economists, since the e®ect of income on crime rates is not even theoretically determined in an Ehrlich's type model, this result seems to be almost a stylized fact for criminologists and sociologists used to the international comparisons of crime rates, and to the discussion of the links between crime and development. Burnham (1990, p.44), for example, in trying to set an agenda for the contemporary study of crime and development, argues that "evidence as exists seems to suggest that development is indeed probably criminogenic". In the same lines, Stack (1984, p.236), when trying to select control variables to include together with a measure of inequality in his regression, decides to include the "level of economic development, a factor found to be related positively to property crime rates in the previous cross-national research". Other papers cited in Table 2 also present arguments in this direction, together with intellectual roundabouts that try to rationalize these results.

Nevertheless, these results may have an explanation far more simple than the industrialization induced social disintegration usually suggested in the sociological literature. One major statistical problem is systematically overlooked in the cross-national studies discussed here: the international comparison based on o±cial data on crime rates. O±cial data is known to greatly underestimate actual crime rates, and this can constitute a serious problem if the degree of underestimation is correlated with the characteristics of the country, including development related variables. If this is really the case, the evidence cited above can not be seriously taken into account until one is able to determine the degree of bias introduced by the underestimation of crime rates in o±cial data, and the correlation of this underestimation with the measures of development. Some of the previous studies acknowledged this problem and its potential severity and tried to concentrate the analysis on crimes thought to be less subject to it (Fajnzylber et all.. [1998] center their discussion in homicides), while most ignored it completely (Krohn and Wellford, 1977; Krohn, 1978; Stack, 1984).

In the next section, we use a new cross-country data set, based on victim survey data, and a traditionally used data set, based on o±cial records, to analyze the characteristics of the underreporting of crimes in the o±cial data and the kind of bias that its use may introduce.

4 The International Data on Crime Rates and its Limitations

4.1 The Data

There are few sources of data on crime rates for di®erent countries, and, until very recent years, all these sources contained only information based on o±cial records.

In the end of the 80's and beginning of the 90's, a new data set based on victimization data began to be put together by a group of di®erent institutions. This data set constitutes today the International Crime Victim Survey (ICVS), a survey conducted by a group of international research institutes under the coordination of the United Nations Interregional Crime and Justice Research Institute (UNICRI). It contains data from selected countries for the years 1989, 1992 and/or 1996/7. Today this data is available as a cross section with the averages for each country in all the surveys in which it was included.

This data base contains the obvious advantage of not being contaminated by the reporting problem present on the o±cial data, but it has the disadvantage of, up to now, only being useful as a cross-section[2]. So, some of the other data bases available, based on o±cial records, still keep their relevance for allowing a reasonable exploration of the panel feature of the phenomenon. It would thus be interesting to know how serious is the reporting problem in o±cial data and wether it is possible to overcome it.

To address this question, we use the United Nations Survey of Crime Trends and Operations of Criminal Justice Systems (UNCS). This is a data set created by the United Nations with information related to several crime and justice related variables based on o±cial records. Several countries and years are irregularly covered, in the period between 1971 and 1994.

We concentrate our analysis on the three types of crimes that can be compared across the victim survey (ICVS) and the o±cial records survey (UNCS). The de¯nitions of these crimes are presented below, together with the way in which the UNCS data was made compatible with the ICVS.

² Thefts: Thefts of bicycle or motorcycle, other personal thefts, pick-

[2] The panel feature of this data can not be explored because the time span is still very short and observations are very irregularly distributed between countries and time periods.

pocketing and car crimes on the ICVS. Thefts and major thefts on the UNCS.

² Contact crimes: Robberies, sexual incidents and/or threats/assaults on the ICVS. Major assaults, assaults, rapes and robberies on the UNCS.

² Burglaries: Burglaries and attempts on the ICVS. Burglaries on the UNCS.

Table 3 presents some descriptive statistics of the two data sets. The numbers are extremely di®erent. Comparing the cross country averages from the ICVS with the ones from the UNCS (based on a within country average from 89 to the last year available), we have the following numbers: according to the o±cial records, 1.40% for thefts, 0.35% for contact crimes, and 0.52% for burglaries; according to the victim survey, 24.81% for thefts, 7.57% for contact crimes, and 6.57% for burglaries. Although the magnitude may be surprising, the underestimation present on the o±cial data, as we said before, was already expected. It does not necessarily constitute a problem on itself if it is not related to the countries' characteristics.

In terms of the cross-country di®erences on crime rates, it is interesting to note that the o±cial data seems to increase the dispersion of the cross-country distribution in relation to its mean: while the ratio of the standard error to the mean is between 1.4 and 1.6 for the three types of crimes in the UNCS data, it is between 0.3 and 0.5 in the ICVS data. This tends to increase the relative di®erences among countries in the o±cial records in relation to the victim data. Besides, the correlation among the di®erent types of crimes is smaller in the o±cial data than in the victim survey data. Together with the relation between the standard errors and the means, it suggests that there is some noise added when we go from the victim survey to the o±cial data. Anyway, even the victim survey shows that crime rates can be quite distinct across countries, with some countries having up to 4, 10 and 20 times higher rates than others for, respectively, thefts, burglaries and contact crimes. This illustrates the relevance of the problem that we are trying to analyze and, again, we think that a natural ¯rst step is to try to relate these di®erences with di®erences in levels of economic development.

We now present some evidence on the di®erent conclusions that are generated when each of these two alternatives types of data is used.

4.2 Cross-Section Analysis

As an exploratory approach, we run cross section regressions of the three types of crimes, for the two data sets, on our variables of interest and on a set of control variables. The UNCS data used is the average for each country of the crime rates between 1989 and the last year available. The basic specification of the regressions is:

$$CRIME_i = \beta_0 + \beta_1.GDP_i + \beta_2.GDPRATIO_i + \beta_3.URB_i + \qquad (1)$$

$$+\beta_4.POL_i + \beta_5.EDUC_i + \beta_6.GROWTH_i + \beta_7.CHR_i + \beta_8.MUS_i + \varepsilon_i;$$

where: CRIME stands for the natural logarithm of the different measures of crime rates (percentage of the population victimized); GDP is the natural logarithm of the GDP per capita; GDPRATIO is our measure of inequality; URB is the percentage of the population living on urban areas; POL is the natural logarithm of the percentage of policemen in the population; EDUC is an index of education; GROWTH is the average GDP per capita growth in the period; and CHR and MUS are dummies indicating the religious majority in the population (Muslim and Christian, respectively)[3]. The Appendix A presents the description and source of these variables.

The first three right hand side variables are the development related variables that constitute our main interest. The religion and education variables are introduced as controls for possible taste shifters that may be correlated with economic development itself. The police variable is a natural control for the crime prevention measures taken by the different countries, and the growth variable is another dimension of economic performance that may also affect crime rates.

[3] The coefficients have the following interpretation: for GDP and POL they are simply elasticities; for GDPRATIO and URB, the relative change on the dependent variable given a one unit change in the independent variable (a one time increase of the GDP of the 20% richest of the population in relation to the GDP of the 20% poorest or 1% more of the population living in an urban area); for the religion dummies, the relative increase in crime if the country has a majority of that religion; and for EDUC (and HDI, that will be used later on), as the variable is an index between 0 and 1, the easier interpretation is to think as the % change in crime for a 0.01 increase on the index. Besides, it is important to keep in mind that these are percentage and relative changes on the rates of crimes, not absolute changes in its level.

We run ¯ve speci¯cations of this equation. We begin including only GDP, GDPRATIO and URB, and then, consecutively, include the police variable, the education index, the growth variable, and the religion dummies. Tables 4 (a), (b), and (c) present these regression for, respectively, thefts, burglaries, and contact crimes. The ¯rst ¯ve columns in each table are related to the o±cial data and the last ¯ve to the victim survey data.

Many of the estimated coe±cients are not statistically signi¯cant in any of the speci¯cations adopted, but still there are a couple of interesting results worthy of note in these tables[4].

In the victim survey data, 10 out of 15 coe±cients on the GDP are negative, and only two are signi¯cant (both negatives). All the coe±cients on the GDPRATIO are positive and statistically signi¯cant, for all types of crimes, and all the coe±cients on URB are positive, and 9 are signi¯cant (8 out of 10 for burglaries and contact crimes).

For the o±cial data cases, 14 out of 15 coe±cients on the GDP are positive, 8 of which are signi¯cant. All the coe±cients on the GDPRATIO are positive, and 7 are signi¯cant. 10 of the coe±cients on URB are negative, and only one is signi¯cant (positively); and 8 out of 9 coe±cients on EDUC are positive, and 3 are signi¯cant.

It seems fair to say that the two data sets describe very di®erent pictures regarding the relation among crime rates and income per capita, inequality, degree of urbanization, and level of education. The victim survey data suggests that crime rates generally increase with inequality and urbanization, and are not signi¯cantly a®ected by income level (if there is any e®ect in this direction, it seems to be negative). The o±cial records data suggests that crime rates increase with income per capita, income inequality, and education, but that they are not signi¯cantly a®ected by the degree of

[4] There is a well known problem of endogeneity of the police variable here (see, for example, Levitt, 1997). As we did not ¯nd a good instrument for it (share of government spending on GDP and other variables were tried), we chose to present the equations with and without the POL variable included on the right hand side. As can be seen from the tables, most of the coe±cients on the other variables change only slightly when POL is excluded from the regression, and, more than that, there is almost no change at all on the qualitative results (in terms of signs or signi¯cance of the coe±cients). Thus, we do not think that the endogeneity problem is interfering in any considerable way on our results. In what follows, we ignore the coe±cients on the police variable, since we do not have any particular interest on them. Just for the record, it is interesting to note that they are negative in all the speci¯cations adopted, although signi¯cant only in a couple of them.

urbanization.

These results indicate that the reporting problem present in the official data does not work in a random fashion, or, in other words, it introduces systematic biases on the estimates obtained from this kind of data. The radically different conclusions obtained from the two data sets, particularly in relation to income level, seem to support the hypothetical relation between underreporting and development level mentioned before. Even more, this relation seems to be serious enough to compromise the interpretation of the coefficients on development related variables obtained from official data regressions, as the ones discussed on section 3.

4.3 The Determinants of the Reporting Rate

The previous section indicates the importance of the underreporting of crimes on official data, and strongly suggests that it may be affected by variables related to the development level of a country[5]. If we assume that the victim survey data represent the "real" crime rate of the different countries, or, at least, that its deviations from it are not correlated with the exogenous variables used, we can compare the two different data sets used in the cross section regressions to analyze the relation between the reporting rate and our right hand side variables.

We do this by running the following regression for the three types of crimes:

$$RRATE_i = \alpha_0 + \alpha_1 \cdot GDP_i + \alpha_2 \cdot EDUC_i + \alpha_3 \cdot URB_i + \varepsilon_i, \qquad (2)$$

where RRATE is the natural logarithm of the reporting rate of the different crimes (ln[UNCS rate/ICVS rate]).

GDP per capita is the most commonly used indicator of development level, and it is highly correlated to some omitted variables that are probably very important in determining the reporting rate (institutional development,

[5] The analysis of the differences between data from official records and from surveys is a recurrent subject in applied criminology research. References in this area include Kitsuse and Cicourel (1963), Skogan (1976), Cohen and Land (1984), Biderman and Lynch (1991), Figlio (1994), O'Brien (1996), Levitt (1998), and many others. Although the topics covered in this literature are the most diverse ones, the discussion is almost always centered on national data (where the problem is most likely less serious), and nobody addresses exactly the same problem that we are trying to address here.

degree of law enforcement, corruptibility of the police, and so on). EDUC may be important in determining the reporting rate basically through knowledge of individual rights, and URB may be important in determining the cost of access to a police department or law related o±ce, as well as the ability of the information to navigate the system, from where the crime was ¯rst registered to the central o±ce where statistics are collected. These three variables are the obvious candidates to determinants of crime reporting rates.

We run this regression and a regression of the reporting rate only on a constant and GDP for the three types of crimes[6]. The results are shown in Table 5, and they are overwhelming: GDP, EDUC and URB explain 76% of the underreporting for thefts, 69% for burglaries, and 45% for contact crimes. Indeed, despite the fact that EDUC is signi¯cant in one equation and barely signi¯cant in another, GDP does almost all the job alone: it explains alone 75% of the underreporting for thefts, 61% for burglaries, and 45% for contact crimes. Countries with higher income per capita have signi¯cantly and systematically higher reporting rates. Figures 1, 2, and 3 plot the RRATE for the di®erent countries against their GDP for, respectively, thefts, burglaries, and contact crimes. The close positive association between the two variables is clear in all three graphs.

These results show where the so well documented positive relation between "development" and crime rates comes from: it is simply a product of the positive correlation between income levels and reporting rates. In other words, all that we can say at this point is that developed countries report more crimes (as a percentage of the total number of crimes), and no evidence presented until now suggests that developed countries actually have higher crime rates. All conclusions from the studies cited in section 3 were seriously harmed by the use of o±cial records data. This result also helps to understand the fact that, in these same studies, the only case for which there was no consistent positive relation between "development" and crime rates was homicide/murder. It is most likely that the "elasticity" of the reporting rate in relation to development will be much smaller for homicide/murder than for the other kinds of crimes, since for the former even if the parties involved (relatives or friends of the victim) are not interested in reporting

[6] The victim survey rate of burglaries for Finland is slightly smaller than the rate calculated from the o±cial data (UNCS). Since this was the only case for which this happened, we think that it is probably due to some minor measurement error, and we ignore this problem completely.

the crime, it is very di±cult to avoid it (the cause of death has always to be indicated, and, if it is homicide/murder, it generally has to be reported to the police). Besides that, the di®erence in the results between the U.S. and the international studies seems also to go in the direction that should be expected, since common sense would suggest that reporting rates vary much more across countries than within countries.

Despite this serious problem in the use of o±cial data on crimes, the International Crime Victim Survey is still a very recent data set to allow the exploration of the time dimension of the changes on crime rates. If one wants to take this into account at least to some extent, hope will still rest on o±cial data sets, like the UNCS one. For this reason, in the next section we suggest a way of "correcting" the o±cial data with the information obtained from the cross section of victim data, such that the "reporting rate problem" is taken into account. The idea is to understand under what conditions, observing only one cross-section of reporting rates, we would be able to estimate the "underreporting structure" and, with that in hand, eliminate the "bad variation" in the o±cial data. If these conditions are not very strict, they will allow the meaningful use of the panel data set from the UNCS, without contamination from the "o±cial data bias". In the last three parts of the section we apply this strategy to the UNCS data, discuss the results, and compare them with the results obtained from a larger panel based on o±cial homicide rates.

5 An Alternative Use of the O±cial Data

5.1 Econometric Approach

Suppose that crime rates are determined according to the following equation:

$$\mathbf{Y}^* = \mathbf{X}.\theta + \boldsymbol{\varepsilon}; \tag{3}$$

where $\mathbf{Y}^*$ stands for the logarithm of the crime rate of a speci¯c type of crime, $\mathbf{X}$ is a vector of country's characteristics, and $\boldsymbol{\varepsilon}$ is an error term for which $Cov(\boldsymbol{\varepsilon}; \mathbf{X}) = 0$ (bold letters denote random vectors or variables).

The only data observed on a panel basis is the o±cial data, that is the "true" data plus a "reporting error":

$$Y = Y^{*} + \upsilon. \tag{4}$$

The reporting error, as the evidence presented on the preceding sections suggests, is assumed to be correlated with the country's characteristics, such that $Cov(\upsilon, X) \neq 0$. For the usual reasons, if we regress Y on X we get a biased estimator of θ, for which $E(\hat{\theta}|X) = \theta + (X'X)^{-1}.X'E(\upsilon|X) \neq \theta$.

If we could obtain an estimator of υ such that $E(\hat{\upsilon}|X) = E(\upsilon|X)$, we could build the series $(Y - \hat{\upsilon})$, and regress it on X to obtain an unbiased estimate of θ. The only hope in this direction lies with the cross section observations available on the victim survey data (from the ICVS data set). The comparison of this data with the UNCS data (based on official records) allows us to build a vector υ_t of cross section observations of the reporting error at a given point in time. If, additionally, the joint distribution of υ and X is invariant across countries and time, this single cross section will allow us to obtain all the relevant information regarding the correlation between υ and X. Maintaining this assumption, and supposing that υ and X are jointly normally distributed, we have that

$$E(\upsilon|X) = X.\gamma, \tag{5}$$

where γ is the vector of coefficients of the linear regression of υ on X[7]. In this case, the projection of the cross section vector υ_t on the corresponding matrix X_t will, given our invariance assumption, give us an unbiased estimate of γ. We can then go on to construct $\hat{\upsilon} = X.\hat{\gamma}$ for all the periods and countries covered by the official data, with $E(\hat{\upsilon}|X) = X.E(\hat{\gamma}|X) = X.E(\hat{\gamma}|X_t) = X.\gamma = E(\upsilon|X)$.

With this estimate of υ in hand, the official data Y can be corrected and an unbiased estimate of θ may be obtained from the regression of $(Y - \hat{\upsilon})$ on X[8]. We now turn to the application of this strategy to our data set.

5.2 Estimation

We apply the approach described in the previous section to the UNCS data set, using the cross section from the ICVS to construct the vector υ_t.

[7] Where X includes the unit vector.

[8] A completely analogous argument, based on the probability limit of the estimated coefficients, applies to justify the use of this strategy together with estimation techniques that rely on asymptotic properties, as the GLS one used in the next section.

All the right hand side variables in equation 1 are also included in the X here. Some of these variables, because of the availability of data or because of the own nature of the characteristic being measured, are country specific variables, in the sense that they change from country to country, but they are constants for a given country across the periods of time under analysis. These variables in equation 1 are inequality (GDPRATIO), degree of urbanization (URB), level of education (EDUC), and religion majority (CHR or MUS). The first three variables are variables that change significantly throughout a country's development process, but that tend to be fairly constant for the majority of countries during not very long time periods, as the one in our case (less than 20 years). In relation to inequality particularly, that may thought to be less stable, Deininger and Squire (1996) have concluded, after extensively documenting the methodology and availability of international data, that "changes in the Gini coefficient of inequality tend to be small" compared to changes in other economic variables (Deininger and Squire, 1996, p.587). The time and country varying variables in our X are, then, income per capita (GDP), number of policemen per capita (POL), and rate of growth (GROWTH).

As the main interest here is on the effect of "structural" differences among countries on their crime rates, it would also be interesting to include some kind of average or time invariant measure of development for each country, in order to allow the model to distinguish between the effect of transitory changes on income and structural or permanent changes in the level of development. For this reason we also include in the right hand side the Human Development Index (HDI) calculated by the United Nations Development Program (the Appendix A describes this index). This index is a relative measure highly correlated with average income levels of the different countries, but it also explicitly takes into account two other dimensions of development (life expectancy and education).

The characteristics X can thus be divided into two subsets, V and F, where the typical vector of V is the time and country variant v_{it}, and the typical vector of F is the country variant and time fixed f_i. We estimate this model with country specific variables in two different ways. Initially, the panel data set is pooled together and we run a simple OLS regression in the whole data much in the same way as we did with equation 1. This amounts to assuming that the error term ε_{it} in equation 3 is i.i.d. both across countries and time. We allow then the error to be correlated across time by assuming $\varepsilon_{it} = \rho_i + \omega_{it}$, where ω_{it} is assumed i.i.d. across i and t, and ρ_i is assumed i.i.d. across i. This random effects model is estimated using a GLS procedure, as described, for example, in Hsiao (1986, p.50-52)[9].

In relation to the estimation of β and the correction of Y discussed in the previous section, two main concerns guide our approach. We want to eliminate the correlation between X and υ from the official data equation, but we want to do so with some confidence that the kind of variation that we are eliminating is really the one that we want to eliminate. In other words, we want γ to be estimated with some precision, and this constitutes a problem since the cross section that we have available for υ is a small sample, and some of the variables included in X are highly correlated with each other. We opt then to restrict the X's included on equation 5 only to those more clearly and intuitively related to the reporting rate and, finally, we end up using again the specification adopted in equation 2. The estimated γ is then used to correct the observed Y in the way described in the previous section. The equation finally estimated is:

$$CRIME_{it} - \beta_0 - \beta_1.GDP_{it} - \beta_2.EDUC_i - \beta_3.URB_i = \tag{6}$$

$$= \theta_0 + \theta_1.GDP_{it} + \theta_2.GDPRATIO_i + \theta_3.URB_i + \theta_4.POL_{it} +$$

$$+\theta_5.EDUC_i + \theta_6.GROWTH_{it} + \theta_7.CHR_i + \theta_8.MUS_i + \omega_{it}.$$

5.3 Analysis of the Results

The results of the regressions of the corrected crime rates on different sets of exogenous variables are presented on Tables 6 (a), (b), and (c), for, respectively, thefts, burglaries, and contact crimes[10]. For purpose of comparison,

[9] Two points are worth of note here. First of all, the presence of individual specific variables (f_i) does not allow this model to be estimated using the fixed effects approach (ρ_i and f_i can not be separately identified). Other important point is that the consistency of the GLS estimator for the coefficients on the f_i's rests on asymptotics on the number of countries, not on time periods.

[10] The UNCS data base is very irregular in terms of countries and variables covered in the different years, what makes its use very difficult if one wants to treat each year as one

we also present in Tables 6 (a), (b), and (c) the coe±cients estimated before, from the cross sections on the uncorrected o±cial data. The ¯rst six columns in each table present the results for the pooled OLS regression, while the six last columns present the GLS random e®ects estimates. The numbers in each column indicate the set of exogenous variables included, with 6 indicating all the exogenous included, and 1 indicating the shortest speci¯cation (only GDP, GDPRATIO, and URB included).

Apart from few cases, the signi¯cant coe±cients are quite similar when we compare the OLS and GLS estimates. Thus, we do not distinguish between them in most of the following discussion. Also, our main interest is still centered on the coe±cients on GDP, GDPRATIO, URB, and HDI, and the other variables were included mainly as controls for e®ects that we do not want to analyze. We also ignore these controls in most of our discussion.

Inequality (GDPRATIO) has a positive and signi¯cant e®ect on basically all types of crimes, for all speci¯cations adopted. Its e®ect seems to be smaller for thefts than for burglaries and contact crimes.

The coe±cient on development (HDI) has a negative sign in all the equations estimated, and it is signi¯cant in 18 out of 30 equations. Another evidence that the e®ect of "structural" development di®erences in crime rates is negative is the fact that, in speci¯cation 1 (when HDI is dropped out of the equation), the coe±cient on GDP turns from negative non-signi¯cant to negative signi¯cant or from positive to negative in all the cases. For burglaries and contact crimes, where GDP is not signi¯cant in speci¯cations 2-6, it becomes signi¯cant in 1. For thefts, where GDP is positive in speci¯cations 2-6, it becomes negative in 1. What is happening is that when we drop HDI out of the regressions, GDP concentrates the e®ects of both permanent and transitory changes on income/development levels and, thus, its coe±cient is pushed further on the negative direction. Another point that this evidence suggests is that it may be very important to distinguish between permanent and transitory changes on income in terms of its consequences on crime rates. At least for thefts, transitory increases on income per capita seem to increase crime rates, while permanent changes on development levels seem to decrease

period individually. To implement the panel estimation and to increase the cross country comparability of the data, we formed three periods with the UNCS data: 75-83, 84-88, and 89-94. Averages for the subperiods were calculated for each country and this data set with three points in time was used in the estimation; in the case of burglaries, only the two last periods are available in the UNCS data set.

them[11]. This feature of the relationship could not possibly be uncovered from a cross section type of analysis on the victim survey data.

Finally, degree of urbanization (URB) affects positively crime rates in nearly all cases, but it is significant only for a couple of cases on burglaries and for all cases on contact crimes.

If we look at the results from the perspective of the different types of crimes, we also see interesting patterns. Thefts seem to be positively affected by inequality and short run movements in income per capita, but negatively affected by development; urbanization does not seem to be very important in its determination. Burglaries are positively affected by inequality and, maybe, by urbanization; it also seems to decrease – not very significantly – with development. Contact crimes increase with inequality and urbanization, and decrease with development. The results support the common view in criminology that different kinds of crimes should be analyzed separately, for they have a different nature and react distinctly to changes on the exogenous variables.

The quantitative implications of the HDI and GDPRATIO coefficients are also worth of note. Looking at specification 2 of the pooled regression estimates, we have that a one time increase in the GDP per capita of the richest 20% in relation to the GDP per capita of the poorest 20% would imply an increase of 3.4%, 13.1%, and 10.1% in the rates of, respectively, thefts, burglaries, and contact crimes; a 0.01 gain in the Human Development Index (HDI), on the other hand, would make a country reduce its rates of theft, burglary, and contact crimes by 3.3%, 4.0%, and 3.6%. This means, for example, that inequality alone would tend to make a country like Brazil have theft rates 80% bigger than countries like U.S. or England, or 50% bigger than countries like Chile; development would be able to explain 40% more thefts in Brazil than in U.S. or England, and 30% more than in Chile. In terms of burglaries, inequality would make Brazilian rates roughly 4 times bigger than American or English rates, and 3 times bigger than Chilean; development would make these numbers, respectively, 1.5 and 1.3. For contact crimes,

[11] Although maybe apparently strange, this result may be consistent with a model of criminal behavior as a life-cycle occupational choice problem, with a fixed cost of moving between legal and illegal sectors, and with a less then unitary elasticity of the income on the illegal sector to the income on the legal sector. In this case, this effect should not be very strong in "non-economic" crimes (rapes, passion crimes, and the like), and this is exactly what Table 6 (c) suggests.

these numbers would be roughly 3.5 and 2.5 for inequality, and 1.5 and 1.3 for development. Sensible and non trivial e®ects can be perceived from the numbers on Tables 6(a), (b), and (c).

Thus, the use of the o±cial data panel, once taken into account the reporting problem, seems to still be possible and useful, and to shed some light on the di®erent responses of the di®erent types of crimes, and on the importance of the distinction between transitory and permanent changes on the economic conditions.

5.4 Further Evidence from Homicide O±cial Data

As discussed before, the time dimension of the UNCS data set is quite limited. We thus would like to have some additional independent evidence that the e®ects captured and discussed in this section are not spurious consequences of the small variation of our sample in this dimension together with the procedure applied to correct the data.

To attain this goal, we make use of o±cial statistics on homicide rates, that are continuously published by the World Health Organization for a large number of countries in a reasonably regular annual basis (the Appendix A describes the variable used). Sections 3 and 4 suggested that homicide rates seem to be much less subject to reporting problems than other types of crimes; we take this as a given here and use 23 years of observations of homicide rates for 22 countries as a pattern of comparison for the results already obtained[12].

Basically the same speci¯cations discussed in the previous subsection are used in the homicide regressions, with only two minor changes. The variables POL and MUS are excluded, since there are no observations for number of policemen for such a long period of time and number of countries, and there are no Muslim countries in our new sample. The exclusion of POL is probably not harmful, since the results so far suggest its approximate orthogonality in relation to the rest of the independent variables. The other di®erence is that, given the greater number of time observations and the annual frequency of the data, we also run a regression that assumes a common AR1 process for the disturbances, so that, at least to some extent, we take into account

[12] The important point here is that any bias still present in o±cial homicide rates will move the results away from the ones previously obtained, so that an eventual consistency should be regarded as a quite strong evidence in support of our approach.

the potential problem of autocorrelation in the residuals. The results of this estimation are presented in Table 7, with each block of five columns containing the different specifications for each one of the three different estimation techniques.

The coefficient on HDI is always negative, and significant in approximately half the cases. The one on GDP changes sign with the estimation assumption, and it is only significant in the Pooled Regression. In this case, as before, it changes sign as HDI is dropped out from the regression; in the Random Effects estimates, GDP is always negative and non significant; and in the AR1 case, GDP is always positive and non significant, but both the coefficient and the t statistic decrease sharply to close to zero as HDI is excluded. Inequality, on its turn, is still the most consistent effect: the coefficient on GDPRATIO is positive in all the cases, and significant in 13 out of 15 specifications. URB is always negative, but significant only for the pooled regression.

The results are generally consistent with the main conclusions drawn in the previous parts of this section: inequality is the variable most consistently related to homicide, and the effect of development, if anything, seems to be negative, although transitory changes in income seem to have an effect different from permanent ones. Besides that, the order of magnitude of the coefficients estimated here is also extremely similar to the one of the coefficients on Tables 6 (a), (b) and (c), suggesting that our correction procedure does not induce any spurious correlation among the variables of interest.

We evaluate this evidence generally as being strongly in support of the procedure suggested in the beginning of this section. We do not argue that they give proof or a definitive answer in this direction, but we do argue that as the only informal comparison possible, the consistency is clear, despite the different frequency, size and composition of the sample.

6 Conclusions

We presented here strong evidence that the reporting rate of crimes is highly correlated with measures of development of a country, especially income per capita. This important result casts serious doubts on the conclusions obtained in practically all the previous studies on international comparisons of crime rates (discussed in section 3), that systematically found positive correlations between crime rates and "development". The results from section 4 show that the idea that development is criminogenic is false, and it is driven basically by the correlation between "development" and reporting rates.

Despite this fact, we argue that the use of the UNCS data may be potentially useful, for it has variations in the time dimension of crime rates that are not present on the ICVS data set. For this reason, section 5 proposes and applies an approach that tries to correct the o±cial data with the information available from the cross section of victim survey data. The results of the panel data regressions on the corrected data show that inequality has a positive e®ect in all types of crimes, and it is apparently the single factor more closely and consistently related to crime. Development seems to decrease crime rates, although short run increases on income may increase crime, depending on the type of crime. Other variables a®ect di®erently the various types of crimes, stressing the importance of the distinction among these categories in any analysis. The additional evidence presented, from a larger panel of o±cial homicide data (supposedly not so seriously contaminated by the measurement problem), also support these conclusions.

We think that the use of the corrected panel revealed itself important for at least three reasons: ¯rst of all, the potentially distinct e®ects of changes in the development level and in the short run income seem to be important for understanding the incidence of certain types of crimes; in second place, the importance of inequality in determining crime rates is con¯rmed, for its e®ect seems to be even stronger in the panel estimation in comparison to the cross sections of section 4; and ¯nally, the general consistency of the results obtained suggest that this correction approach may also be useful for within country analysis, where it appears to be common the existence of a long panel of o±cial records data (states or metropolitan areas) together with a cross section or short panel of victim survey data. Although the correlation between the economic variables and the reporting rates is not necessarily so strong for di®erent regions of the same country, a systematic investigation of the question in this case has also to be done, before the results based on o±cial records are taken seriously into account.

Even though some of these conclusions may be subject to posterior con¯rmation, we believe that at least two main results of our analysis { that were not settled in the previous literature { are beyond any dispute: the careless use of o±cial data in international studies may lead to grossly wrong conclusions, and income inequality and criminality are two phenomena intimately linked.

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A Appendix: Definition of Variables

- Income: Real GDP per capita in constant dollars adjusted for terms of trade (from 1975 to 1992), from the Penn World Tables, Mark 5.6.

- Inequality: Ratio of the GDP per capita of the richest 20% to the GDP per capita of the poorest 20%. The GDP per capita for these subsets of the population (average from 1980-94) was taken from the United Nations Development Program (UNDP) statistics. This seems to be the statistic that is closer to the kind of inequality that is theoretically thought to be associated with crime (see, for example, Chiu and Madden, 1998).

- Degree of Urbanization: Urban population as a percentage of total population (1995), from the UNDP statistics.

- Human Development Index: Index calculated by the UNDP combining relative indicators of life expectancy, income and educational attainment.

- Number of policemen: Police force as a percentage of the total population, from the UNCS.

- Education: Education index calculated by the UNDP.

- Growth rate: Average annual rate of growth of the real GDP measure described above.

- Religion dummy (MUS or CHR): Dummy variables assuming value 1 when at least 60% of the population belongs to the religion in question (respectively, Muslim or Christian), from CIA data.

- Homicides: Annual homicides as a percentage of the population (from 1970 to 1992), calculated from the World Health Organization data on number of deaths due to "homicide and injury purposely inflicted by other persons, injury resulting from operations of war, and injury due to legal intervention" (1995).

Table 1 - Summary of the Evidence on the Effect of Inequality* on Crime Rates

Study	Unit/Dimension of Analysis	Type of Crime	Conclusions
Eberts and Schwirian (1968)	SMSA's / Cross-section	Total crime (official data)	Positive effect
Danzinger and Wheeler (1975)*	U.S. national data / Time series	Burglary (official data) Assault Robery	No significant effect No significant effect Positive effect
Danzinger and Wheeler (1975)*	SMSA's / Cross-section	Burglary (official data) Assault Robery	Positive effect Positive effect Positive effect
Jacobs (1981)*	SMSA's / Cross-section	Burglary (official data) Grand larceny Robbery	Positive effect Positive effect Positive effect
Blau and Blau (1982)*	SMSA's / Cross-section	Murder (official data) Rape Robbery Assault	Positive effect No significant effect No significant effect Positive effect
Messner (1982)*	SMSA's / Cross-section	Murder (official data)	No significant effect
Carrol and Jackson (1983)	U.S. cities / Cross-section	Burglary (official data) Robbery Crime against the person	Positve effect Positve effect Positve effect
Williams (1984)*	SMSA's / Cross-section	Homicide (official data)	No significant effect
Bailey (1984)*	U.S. cities / Cross-section	Murder (official data)	No significant effect
Stack (1984)	Countries / Cross-section	Property crime (official data)	Negative effect
Patterson (1991)	U.S. Neighborhoods / Cross-section	Burglary (victim surv. Data) Violent crime	No significant effect No significant effect
Fowles and Merva (1996)	SMSA's / Panel	Aggravated assault (off. data) Murder Motor vehicle theft Larceny/theft Robbery Burglary Rape	Positive effect Positive effect No significant effect Positive effect No significant effect No significant effect Negative effect
Allen (1996)	U.S. national data / Time series	Robbery (official data) Burglary Vehicle theft	No significant effect No significant effect No significant effect
Fajnzylber et al. (1998)	Countries / Panel	Homicide (official data) Robbery	Positive effect Positive effect
Kelly (1999)	U.S. counties / Cross-section	Violent crime (official data) Property crime Assault Robbery Murder Rape Burglary Larceny Car crime	Positive effect No significant effect Positive effect Positive effect No significant effect Negative effect Positive effect No significant effect No significant effect

Obs.:* - Gini coefficient in 13 of the cases; various different measures in Eberts and Schwirian (1968) and Fowles and Merva (1996).
** - From Fowles and Merva (1996, Table 1, p.167).

Table 2 - Summary of the Evidence on the Effect of Development* on Crime Rates

Study	Unit/Dimension of Analysis	Type of Crime	Conclusions
Wolf (1971)	Countries / Panel	Total crime (official data)	Positive effect
		Larceny	Positive effect
		Murder	Negative effect
Wellford (1974)	Countries / Cross-section	Homicide (official data)	Negative effect
		Sex offence	Positive effect
		Major larceny	Positive effect
		Minor larceny	Positive effect
		Fraud	Positive effect
		Counterfeit	Positive effect
		Drug	Negative effect
		Total crime	Positive effect
Harries (1976)**	U.S. cities / Cross-section	Robbery	No significant effect
		Aggravated assault	Negative effect
		Burglary	No significant effect
		Auto theft	No significant effect
McDonald (1976)	Countries / Cross-section	Juvenile crime (official data)	Positive effect
		Theft	Positive effect
		Property	Positive effect
		Total crime	Positive effect
		Murder	Negative effect
Krohn and Wellford (1977)	Countries / Cross-section	Homicide (official data)	Negative effect
		Property crime	Positive effect
		Total crime	Positive effect
Krohn (1978)	Countries / Cross-section	Homicide (official data)	Negative effect
		Property crime	Positive effect
		Total crime	Positive effect
Decker (1980)**	U.S. cities / Cross-section	Violent crime (official data)	Negative effect
		Property crime	Negative effect
		Viol. crime (vict. sur. data)	Positive effect
		Property crime	No significan effect
Stack (1984)	Countries / Cross-section	Property crime (official data)	Positive effect
Watts and Watts (1981)**	U.S. cities / Cross-section	Major crimes (official data)	Positive ef fect
Blau and Blau (1982)**	SMSA's / Cross-section	Murder (official data)	No significant effect
		Rape	No significant effect
		Robbery	Positive effect
		Assault	No significant effect
Crutchfield et al. (1982)**	SMSA's / Cross-section	Robbery (official data)	Positive effect
		Assault	Negative effect
		Burglary	Negative effect
Messner (1982)**	SMSA's / Cross-section	Murder (official data)	Positive effect
Sampson and Castellano (1982)**	U.S. Neighborhoods / Panel	Theft viol.crim.(vict.sur.data)	Negative effect
Messner (1983),Williams(1984)**	SMSA's / Cross-section	Homicide (official data)	Negative effect
Loftin and Parker (1985)**	U.S. cities / Cross-section	Total crime	Negative effect
		Family crime	Negative effect
		Other primary crime	Negative effect
		Homicide	Negative effect
Messner and Tardiff (1986)**	Manhattan Neighborhoods / Cross-section	Homicide (official data)	Negative effect
Sampson (1986)**	U.S. Neighborhoods / Panel	Theft (victim survey data)	Negative effect
		Personal crime	Negative effect
Patterson (1991)	U.S. Neighborhoods / Cross-section	Burglary (victim surv. data)	No significant effect
		Violent crime	Negative effect
Fowles and Merva (1996)	SMSA's / Panel	Aggrav. assault (off. data)	Negative effect
		Murder	Negative effect
		Motor vehicle theft	Negative effect
		Larceny/theft	Negative effect
		Robbery	Negative effect
		Burglary	Negative effect
		Rape	Negative effect
Allen (1996)	U.S. national data / Time series	Robbery (official data)	Positive effect
		Burglary	Positive effect
		Vehicle theft	Positive effect
Fajnzy lber et al. (1998)	Countries / Panel	Homicide (official data)	No significant effect
		Robbery	Positive effects
Kelly (1999)	U.S. counties / Cross-section	Violent crime (official data)	No significant effect
		Property crime	Negative effect
		Assault	No significant effect
		Robbery	No significant effect
		Murder	No significant effect
		Rape	Negative effect
		Burglary	Negative effect
		Larceny	Negative effect
		Car crime	No significant effect

Obs.:* - Income per capita or (inverse of) incidence of poverty in 20 cases; various different measures in Wolf (1971) and Krohn (1978).
* * - From Patterson (1991, Table 1, p.757).

Table 3 - Descriptive Statistics

	Official Data			Victim Survey Data		
	Theft	Burglary	Contact	Theft	Burglary	Contact
Average	1.40	0.52	0.35	24.81	6.57	7.57
Std Dev	1.92	0.85	0.53	6.88	3.50	3.59
Max	8.12	5.81	3.30	41.80	17.40	21.00
Min	0.00	0.00	0.00	11.60	0.90	2.00
N	82	84	81	46	45	45
Correlations						
Theft	1.00			1.00		
Burglary	0.45	1.00		0.61	1.00	
Contact	0.31	0.20	1.00	0.55	0.74	1.00

Obs.: Data is number of crimes as a percentage of population. Official data is taken from the UNCS data set and victim survey data from the ICVS. For comparability between the two data sets, statistics for the official data are calculated from country averages, from 1989 to the last year available. ICVS data are averages for all the surveys in which the country was included (1989, 1992, and/or 1996/7).

Table 4(a) - Cross Section Regressions for Thefts

	Thefts - Official Data					Thefts - Victim Survey Data				
	1	2	3	4	5	1	2	3	4	5
GDP	1.6937	1.9453	1.8092	2.1377	2.2852	0.0010	0.0951	0.0826	0.1547	0.2599
	0.2658	0.2976	0.3440	0.3802	0.3765	0.1061	0.1284	0.1440	0.1449	0.2040
GDPRATIO	0.0565	0.0522	0.0496	0.0869	0.0714	0.0257	0.0445	0.0453	0.0575	0.0691
	0.0310	0.0347	0.0351	0.0400	0.0451	0.0134	0.0261	0.0275	0.0274	0.0339
URB	-0.0047	-0.0145	-0.0167	-0.0126	-0.0103	0.0083	0.0040	0.0033	0.0060	0.0118
	0.0113	0.0170	0.0173	0.0167	0.0165	0.0053	0.0072	0.0080	0.0078	0.0105
POL		-0.0473	-0.0888	-0.2313	-0.0005		-0.0440	-0.0690	-0.1211	-0.5968
		0.2611	0.2682	0.2692	0.3492		0.1937	0.2278	0.2186	0.4508
EDUC			1.4805	0.1087	-3.6912			0.2780	-0.3340	-1.3839
			1.8279	1.9197	3.1809			1.1582	1.1733	3.2001
GROWTH				-0.0909	-0.1062				-0.0466	-0.0672
				0.0530	0.0630				0.0318	0.0417
CHR					0.5455					0.0775
					0.7713					1.2561
MUS					-1.0594					-0.9698
					0.6959					0.8706
CONST	-15.2039	-16.8458	-16.7839	-19.2787	-17.3334	2.4247	1.6134	1.4791	1.0062	-0.2338
	1.8475	2.1480	2.1672	2.5292	2.9418	0.6736	1.1511	1.3275	1.2976	1.9343
R-Squared	0.72	0.82	0.82	0.84	0.87	0.31	0.42	0.42	0.53	0.62
N OBS	42	26	26	26	26	29	16	16	16	16

Obs.: Numbers below the coefficients are standard errors. For comparability between the two data sets, statistics for the official data are calculated from UNCS country averages, from 1989 to the last year available. Victim survey data are averages for all the ICVS surveys in which the country was included (1989, 1992, and/or 1996/7). Dependent variable is the log of the number of thefts as percentage of the total population. Independent variables are log of the GDP per capita adjusted for terms of trade; ratio between GDP per capita of the 20% richest and of the 20% poorest; percentage of population living in urban areas; log of the number of policemen as a percentage of the population; relative indicator of education; average growth rate of the GDP per capita in the period; and dummies indicating that at least 60% of the population is Christian or Muslim. The big difference on the number of observations as POL is dropped out is due to the irregularity of this variable in the UNCS data.

Table 4(b) - Cross Section Regressions for Burglaries

	Burglaries - Official Data					Burglaries - Victim Survey Data				
	1	2	3	4	5	1	2	3	4	5
GDP	1.4912	1.6577	0.9033	0.8413	0.8737	-0.3844	-0.2630	-0.1450	-0.1520	-0.2171
	0.3445	0.4546	0.4991	0.7026	0.7495	0.1937	0.2212	0.2262	0.2534	0.3926
GDPRATIO	0.0986	0.0962	0.0963	0.0915	0.0958	0.0853	0.1051	0.0969	0.0957	0.0982
	0.0608	0.0881	0.0782	0.0883	0.0986	0.0244	0.0450	0.0433	0.0479	0.0652
URB	-0.0055	-0.0008	-0.0151	-0.0155	-0.0138	0.0222	0.0300	0.0361	0.0359	0.0360
	0.0154	0.0276	0.0251	0.0260	0.0278	0.0096	0.0124	0.0126	0.0136	0.0202
POL		-0.3086	-0.4533	-0.4394	-0.4893		-0.4764	-0.2395	-0.2344	-0.1374
		0.4157	0.3735	0.3979	0.5218		0.3337	0.3580	0.3823	0.8675
EDUC			8.5620	8.8658	9.1312			-2.6308	-2.5710	-1.3388
			3.3285	4.1490	5.4276			1.8199	2.0516	6.1580
GROWTH				0.0112	-0.0084				0.0046	0.0032
				0.0870	0.1086				0.0556	0.0802
CHR					-0.2682					-0.4424
					1.0603					2.4171
MUS					-0.3729					0.1240
					1.2557					1.6753
CONST	-14.7314	-16.9476	-16.7842	-16.4072	-16.9383	2.9985	0.3727	1.6437	1.6899	1.6829
	2.4768	3.4664	3.0797	4.3061	5.3301	1.2295	1.9830	2.0858	2.2689	3.7223
R-Squared	0.54	0.61	0.71	0.71	0.71	0.40	0.54	0.62	0.62	0.62
N OBS	40	26	26	26	26	29	16	16	16	16

Obs.: Numbers below the coefficients are standard errors. For comparability between the two data sets, statistics for the official data are calculated from UNCS country averages, from 1989 to the last year available. Victim survey data are averages for all the ICVS surveys in which the country was included (1989, 1992, and/or 1996/7). Dependent variable is the log of the number of burglaries as percentage of the total population. Independent variables are log of the GDP per capita adjusted for terms of trade; ratio between GDP per capita of the 20% richest and of the 20% poorest; percentage of population living in urban areas; log of the number of policemen as a percentage of the population; relative indicator of education; average growth rate of the GDP per capita in the period; and dummies indicating that at least 60% of the population is Christian or Muslim. The big difference on the number of observations as POL is dropped out is due to the irregularity of this variable in the UNCS data.

Table 4(c) - Cross Section Regressions for Contact Crimes

	Contact Crimes - Official Data					Contact Crimes - Victim Survey Data				
	1	2	3	4	5	1	2	3	4	5
GDP	0.4967	0.3358	-0.0311	0.4226	0.4827	-0.3277	-0.1792	-0.1982	-0.1359	-0.3888
	0.3340	0.3854	0.3810	0.4056	0.3944	0.1522	0.2176	0.2441	0.2666	0.3161
GDPRATIO	0.1580	0.0680	0.0861	0.1448	0.1069	0.0773	0.0952	0.0965	0.1071	0.1726
	0.0532	0.0715	0.0645	0.0646	0.0741	0.0192	0.0442	0.0467	0.0503	0.0525
URB	0.0104	0.0349	0.0216	0.0245	0.0216	0.0178	0.0197	0.0187	0.0210	0.0430
	0.0142	0.0232	0.0216	0.0196	0.0189	0.0076	0.0122	0.0136	0.0143	0.0163
POL		-0.1796	-0.2635	-0.4368	-0.2001		-0.4860	-0.5241	-0.5691	-1.3263
		0.3148	0.2844	0.2701	0.3713		0.3282	0.3863	0.4022	0.6984
EDUC			5.2493	3.2628	0.8391			0.4239	-0.1053	8.0332
			2.3050	2.2868	4.0516			1.9639	2.1584	4.9578
GROWTH				-0.1150	-0.0379				-0.0403	-0.1263
				0.0541	0.0688				0.0584	0.0646
CHR					1.1412					-3.9871
					0.9691					1.9460
MUS					1.4746					-2.2538
					0.8035					1.3487
CONST	-8.0896	-7.9475	-8.5195	-11.7217	-10.2171	3.0327	0.6355	0.4307	0.0219	-4.4531
	2.3693	2.7134	2.4435	2.6768	3.3375	0.9663	1.9507	2.2509	2.3871	2.9968
R-Squared	0.37	0.51	0.63	0.71	0.78	0.46	0.43	0.43	0.46	0.69
N OBS	38	22	22	22	22	29	16	16	16	16

Obs.: Numbers below the coefficients are standard errors. For comparability between the two data sets, statistics for the official data are calculated from UNCS country averages, from 1989 to the last year available. Victim survey data are averages for all the ICVS surveys in which the country was included (1989, 1992, and/or 1996/7). Dependent variable is the log of the number of contact crimes as percentage of the total population. Independent variables are log of the GDP per capita adjusted for terms of trade; ratio between GDP per capita of the 20% richest and of the 20% poorest; percentage of population living in urban areas; log of the number of policemen as a percentage of the population; relative indicator of education; average growth rate of the GDP per capita in the period; and dummies indicating that at least 60% of the population is Christian or Muslim. The big difference on the number of observations as POL is dropped out is due to the irregularity of this variable in the UNCS data.

Table 5 - Cross Section Regressions for the Reporting Rate

	Thefts		Burglaries		Contact Crimes	
	1	2	1	2	1	2
GDP	1.5408	1.5046	1.5840	1.3166	0.9576	0.8448
	0.1775	0.3628	0.2635	0.5151	0.2560	0.4935
EDUC		1.7897		7.5394		4.7883
		2.5317		3.4382		3.4079
URB		-0.0061		-0.0305		-0.0206
		0.0179		0.0227		0.0260
CONST	-16.6977	-17.5865	-16.6249	-18.8926	-12.1487	-14.0422
	1.5574	2.1867	2.3390	2.8366	2.2368	2.9913
R-Squared	0.75	0.76	0.61	0.69	0.39	0.45
N OBS	27	26	25	25	24	24

Obs.: Numbers below the coefficients are standard errors. Dependent variable (reporting rate) is defined as the log of the ratio of official crime rates (UNCS averages from 1989 to last year available) to victim survey crime rates (ICVS averages from 1989, 1992, and/or 1996/7 surveys). Rates are number of crimes as a percentage of total population. Independent variables are GDP per capita adjusted for terms of trade, relative education index, and percentage of population living in urban areas.

Table 6(a) - Panel Regressions for Corrected Data on Thefts

	Pooled Regression						Random Effects					
	1	2	3	4	5	6	1	2	3	4	5	6
GDP	-0.0676	0.4293	0.3110	0.4706	0.5520	0.5456	-0.3258	-0.0483	0.1496	0.3019	0.3606	0.3757
	0.1736	0.2328	0.2698	0.2639	0.2586	0.2643	0.2184	0.2725	0.2888	0.2821	0.2765	0.2842
GDPRATIO	0.0258	0.0344	0.0528	0.0533	0.0503	0.0479	0.0331	0.0360	0.0525	0.0495	0.0476	0.0483
	0.0190	0.0186	0.0231	0.0221	0.0215	0.0227	0.0240	0.0231	0.0246	0.0235	0.0229	0.0244
URB	0.0024	0.0052	0.0022	0.0015	-0.0017	-0.0013	0.0097	0.0123	0.0042	0.0036	0.0019	0.0020
	0.0071	0.0069	0.0086	0.0082	0.0082	0.0083	0.0092	0.0092	0.0101	0.0097	0.0096	0.0097
HDI		-3.2737	-2.1621	-6.2326	-6.2133	-5.9324		-1.8992	-1.8461	-6.5735	-6.7262	-6.6932
		1.0624	1.2425	1.8262	1.8943	1.9448		1.2964	1.3359	1.9668	1.9967	2.0511
POL			-0.0355	-0.0247	-0.0006	0.0057			0.0344	0.0146	0.0232	0.0195
			0.1362	0.1304	0.1273	0.1346			0.1187	0.1167	0.1149	0.1215
EDUC				4.0251	3.5468	3.0361				5.0467	4.8538	4.7644
				1.3706	1.4243	1.7050				1.6123	1.6209	1.9146
GROWTH					-0.0078	-0.0147					0.0035	0.0012
					0.0310	0.0331					0.0278	0.0291
CHR						-0.0678						-0.0828
						0.2893						0.3379
MUS						-0.3907						-0.1257
						0.3953						0.4601
CONST	3.3237	1.4896	1.6494	0.2715	0.2548	0.6049	5.0005	3.9703	2.7492	1.0810	1.0119	0.9798
	1.1686	1.2776	1.5023	1.5124	1.4714	1.6901	1.4629	1.5322	1.6734	1.6834	1.6414	1.8990
R-Squared	0.02	0.09	0.09	0.18	0.19	0.20	0.60	0.60	0.71	0.72	0.71	0.70
N OBS	128	128	89	89	88	88	128	128	89	89	88	88
	Uncorrected Cross Section Coefficients											
GDP		1.6937	1.9453	1.8092	2.1377	2.2852						
GDPRATIO		0.0565	0.0522	0.0496	0.0869	0.0714						

Obs.: Numbers below the coefficients are standard errors. Data refer to averages of the periods 1975-83, 1984-88, and 1989-94 (or last year available). Dependent variable is the log of the number of thefts as percentage of the total population, corrected for the underreporting bias. Independent variables are log of the GDP per capita adjusted for terms of trade; ratio between GDP per capita of the 20% richest and of the 20% poorest; percentage of population living in urban areas; relative indicator of development; log of the number of policemen as a percentage of the population; relative indicator of education; average growth rate of the GDP per capita in the period; and dummies indicating that at least 60% of the population is Christian or Muslim. GDP, GROWTH and POL are the time varying variables. Observations are divided between countries and periods in the following way: in the case of 88 (89) observations, 13 countries have 3 periods of data, 13 (14) coutries have 2 periods, and 23 (22) have 1; in the case of 128 observations, 30 countries have 3 periods of data, 15 countries have 2 periods, and 8 have 1. The R-Squared for the Random Effects case is based on the transformed data. Uncorrected cross section coefficients are taken from Table 4(a).

Table 6(b) - Panel Regressions for Corrected Data on Burglaries

	Pooled Regression						Random Effects					
	1	2	3	4	5	6	1	2	3	4	5	6
GDP	-0.5684	0.0315	0.2665	0.3014	0.2972	0.2996	-0.4990	0.0920	0.1115	0.1396	0.1437	0.1518
	0.2489	0.3925	0.5087	0.5198	0.5318	0.5437	0.2965	0.4489	0.5330	0.5422	0.5544	0.5678
GDPRATIO	0.1260	0.1309	0.1125	0.1139	0.1138	0.1049	0.1183	0.1213	0.1076	0.1095	0.1096	0.1074
	0.0437	0.0429	0.0587	0.0594	0.0601	0.0647	0.0526	0.0513	0.0644	0.0650	0.0657	0.0692
URB	0.0238	0.0246	0.0195	0.0192	0.0192	0.0192	0.0210	0.0230	0.0236	0.0232	0.0230	0.0226
	0.0106	0.0104	0.0158	0.0160	0.0162	0.0166	0.0130	0.0127	0.0179	0.0181	0.0183	0.0185
HDI		-4.0166	-4.4198	-5.6617	-5.7454	-5.4307		-4.1327	-3.7885	-5.0569	-5.0129	-5.0453
		2.0594	2.9392	4.1326	4.4664	4.7296		2.3829	3.1056	4.3270	4.5804	4.8242
POL			-0.3209	-0.3110	-0.3090	-0.2413			-0.3579	-0.3509	-0.3503	-0.3259
			0.2733	0.2768	0.2826	0.3222			0.2260	0.2330	0.2386	0.2803
EDUC				1.3495	1.4358	0.2685				1.5044	1.4527	1.2039
				3.1264	3.5537	4.3681				3.5618	3.8395	4.5526
GROWTH					0.0031	0.0054					-0.0018	0.0014
					0.0581	0.0667					0.0513	0.0599
CHR						0.2585						0.0651
						0.5513						0.5895
MUS						-0.1909						-0.0641
						0.9811						1.0755
CONST	3.9803	2.0196	0.3415	-0.0542	-0.0247	0.6892	3.5995	1.7496	0.8861	0.4334	0.4158	0.6211
	1.7781	2.0108	2.5101	2.6944	2.7815	3.2006	2.1318	2.3454	2.7121	2.9400	3.0199	3.3966
R-Squared	0.24	0.28	0.23	0.24	0.24	0.24	0.76	0.76	0.69	0.67	0.66	0.61
N OBS	70	70	50	50	50	50	70	70	50	50	50	50
	Uncorrected Cross Section Coefficients											
GDP		1.4912	1.6577	0.9033	0.8413	0.8737						
GDPRATIO		0.0986	0.0962	0.0963	0.0915	0.0958						

Obs.: Numbers below the coefficients are standard errors. Data refer to averages of the periods 1984-88, and 1989-94 (or last year available). Dependent variable is the log of the number of burglaries as percentage of the total population, corrected for the underreporting bias. Independent variables are log of the GDP per capita adjusted for terms of trade; ratio between GDP per capita of the 20% richest and of the 20% poorest; percentage of population living in urban areas; relative indicator of development; log of the number of policemen as a percentage of the population; relative indicator of education; average growth rate of the GDP per capita in the period; and dummies indicating that at least 60% of the population is Christian or Muslim. GDP, GROWTH and POL are the time varying variables. Observations are divided between countries and periods in the following way: in the case of 50 observations, 17 countries have 2 periods of data, and 16 have 1; in the case of 70 observations, 30 countries have 2 periods of data, and 10 have 1. The R-Squared for the Random Effects case is based on the transformed data. Uncorrected cross section coefficients are taken from Table 4(b).

Table 6(c) - Panel Regressions for Corrected Data on Contact Crimes

	Pooled Regression						Random Effects					
	1	2	3	4	5	6	1	2	3	4	5	6
GDP	-0.9023	-0.3627	-0.4277	-0.3990	-0.3547	-0.3830	-0.8415	-0.4156	-0.2950	-0.2648	-0.2322	-0.2691
	0.1999	0.2730	0.3068	0.3168	0.3147	0.3039	0.2478	0.3035	0.2899	0.2959	0.2964	0.2958
GDPRATIO	0.0942	0.1006	0.1183	0.1181	0.1133	0.1154	0.0866	0.0894	0.1559	0.1543	0.1488	0.1412
	0.0248	0.0241	0.0344	0.0346	0.0342	0.0336	0.0303	0.0293	0.0379	0.0382	0.0380	0.0377
URB	0.0291	0.0318	0.0234	0.0233	0.0195	0.0182	0.0276	0.0362	0.0236	0.0235	0.0208	0.0171
	0.0081	0.0080	0.0104	0.0104	0.0104	0.0100	0.0108	0.0110	0.0119	0.0120	0.0120	0.0117
HDI		-3.5761	-2.7468	-3.4349	-2.1752	-2.4156		-3.6254	-3.1548	-4.5311	-3.9564	-3.9781
		1.2738	1.4586	2.2666	2.3772	2.3129		1.5253	1.5398	2.4334	2.4594	2.3924
POL			0.2949	0.2971	0.3000	0.3476			0.4357	0.4315	0.4344	0.4552
			0.1544	0.1553	0.1531	0.1575			0.1003	0.1017	0.1018	0.1059
EDUC				0.6776	-0.5704	-0.8132				1.5547	0.7700	0.2317
				1.7015	1.7876	2.0468				2.1173	2.1617	2.3861
GROWTH					-0.0641	-0.0337					-0.0258	-0.0179
					0.0380	0.0382					0.0254	0.0260
CHR						0.7633						0.8967
						0.3351						0.3965
MUS						0.8301						0.6366
						0.4712						0.5788
CONST	7.1877	5.2590	6.0992	5.8569	5.9011	6.0768	6.8245	5.5350	5.1664	4.7302	4.9220	5.3869
	1.3668	1.4936	1.6822	1.7978	1.7692	1.9735	1.6747	1.7303	1.7237	1.8393	1.8314	2.0975
R-Squared	0.31	0.36	0.39	0.39	0.42	0.48	0.83	0.83	0.91	0.91	0.91	0.91
N OBS	115	115	81	81	80	80	115	115	81	81	80	80
	Uncorrected Cross Section Coefficients											
GDP		0.4967	0.3358	-0.0311	0.4226	0.4827						
GDPRATIO		0.1580	0.068	0.0861	0.1448	0.1069						

Obs.: Numbers below the coefficients are standard errors. Data refer to averages of the periods 1975-83, 1984-88, and 1989-94 (or last year available). Dependent variable is the log of the number of contact crimes as percentage of the total population, corrected for the underreporting bias. Independent variables are log of the GDP per capita adjusted for terms of trade; ratio between GDP per capita of the 20% richest and of the 20% poorest; percentage of population living in urban areas; relative indicator of development; log of the number of policemen as a percentage of the population; relative indicator of education; average growth rate of the GDP per capita in the period; and dummies indicating that at least 60% of the population is Christian or Muslim. GDP, GROWTH and POL are the time varying variables. Observations are divided between countries and periods in the following way: in the case of 80 (81) observations, 12 countries have 3 periods of data, 12 coutries have 2 periods, and 20 (21) have 1; in the case of 115 observations, 25 countries have 3 periods of data, 15 countries have 2 periods, and 10 have 1. The R-Squared for the Random Effects case is based on the transformed data. Uncorrected cross section coefficients are taken from Table 4(c).

Table 7 - Panel Regressions for Homicides

	Pooled Regression					Random Effects					AR1 Disturbance				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
GDP	-0.1987	0.3696	0.4021	0.4069	0.5680	-0.0405	-0.0308	-0.0307	-0.0401	-0.0369	0.0303	0.2100	0.2079	0.2678	0.3024
	0.0874	0.1136	0.1165	0.1166	0.1130	0.0604	0.0608	0.0609	0.0611	0.0612	0.1806	0.1931	0.1946	0.2144	0.2099
GDPRATIO	0.0870	0.0802	0.0775	0.0751	0.0504	0.0902	0.0694	0.0686	0.0677	0.0420	0.0926	0.0683	0.0689	0.0690	0.0372
	0.0074	0.0071	0.0074	0.0075	0.0079	0.0249	0.0273	0.0289	0.0288	0.0318	0.0242	0.0245	0.0255	0.0255	0.0281
URB	-0.0114	-0.0069	-0.0099	-0.0102	-0.0087	-0.0122	-0.0052	-0.0060	-0.0061	-0.0045	-0.0111	-0.0046	-0.0036	-0.0038	-0.0017
	0.0030	0.0029	0.0037	0.0037	0.0036	0.0126	0.0127	0.0164	0.0163	0.0154	0.0103	0.0099	0.0142	0.0142	0.0132
HDI		-8.6921	-7.0863	-6.4711	-8.3289		-5.7390	-5.2584	-5.0296	-5.6496		-8.5689	-9.0629	-9.3023	-9.1940
		1.1871	1.7474	1.7636	1.6948		3.8054	7.2146	7.1884	6.7934		3.5650	6.1873	6.1975	5.7643
EDUC			-1.7135	-2.3902	-5.5730			-0.4581	-0.6500	-3.7210			0.4589	0.2199	-4.4858
			1.3689	1.3971	1.3980			5.8426	5.8215	5.8341			4.6954	4.7088	4.8969
GROWTH				-0.0173	-0.0051				-0.0051	-0.0051				-0.0016	-0.0017
				0.0077	0.0075				0.0027	0.0027				0.0024	0.0024
CHR					0.7532					0.6803					0.7655
					0.1041					0.4363					0.3602
CONST	-4.2195	-1.7582	-1.6785	-1.5756	1.0340	-5.6183	-0.8531	-0.7996	-0.7172	2.1764	-6.4032	-0.5439	-0.5798	-0.6592	2.7503
	0.7927	0.8240	0.8260	0.8316	0.8683	1.1522	3.3425	3.4090	3.3965	3.7035	1.8090	2.9394	2.9661	2.9683	3.1988
R-Squared	0.34	0.40	0.40	0.41	0.47	0.93	0.93	0.93	0.93	0.93	0.72	0.74	0.74	0.74	0.76
N OBS	482	482	482	481	481	482	482	482	481	481	480	480	480	480	480

Obs.: Numbers below the coefficients are standard errors. Data refer to years between 1970 and 1992. Dependent variable is log of the number of homicides as percentage of the total population. Independent variables are log of the GDP per capita adjusted for terms of trade; ratio between GDP per capita of the 20% richest and of the 20% poorest; percentage of population living in urban areas; relative indicator of development; relative indicator of education; growth rate of the GDP per capita over the previous year; and dummy indicating that at least 60% of the population is Christian. GDP and GROWTH are the time varying variables. Observations are divided between countries and years in the following way: 16 countries have 23 years of data, 3 coutries have 21 years, one has 20, one has 17, and one has 14; in the case of 481 observations, only 15 countries have 23 years, and one has 22. The AR1 case has always 480 observations because two isolated points in the series (without observations before and after them) are dropped out; the initial observation for each country is used in this estimation with a weight based on the estimated Rho. The R-Squared for the AR1 and Random Effects cases is based on the transformed data.

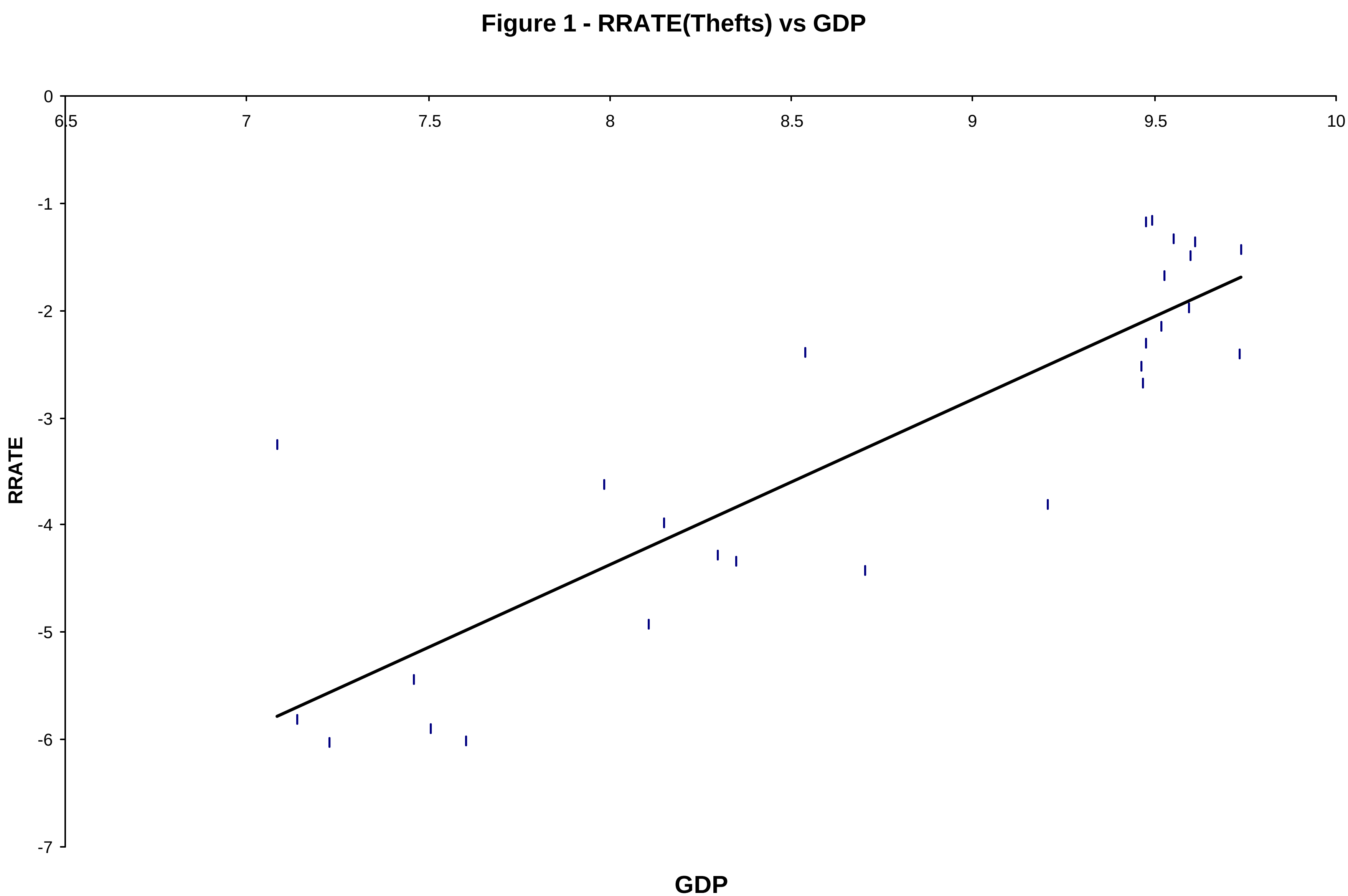
Figure 1 - RRATE(Thefts) vs GDP
0
-1
-2
-3
-4
-5
-6
-7
6.5
7
7.5
8
8.5
9
9.5
10
RRATE
GDP

Figure 2 - RRATE(Burglaries) vs GDP

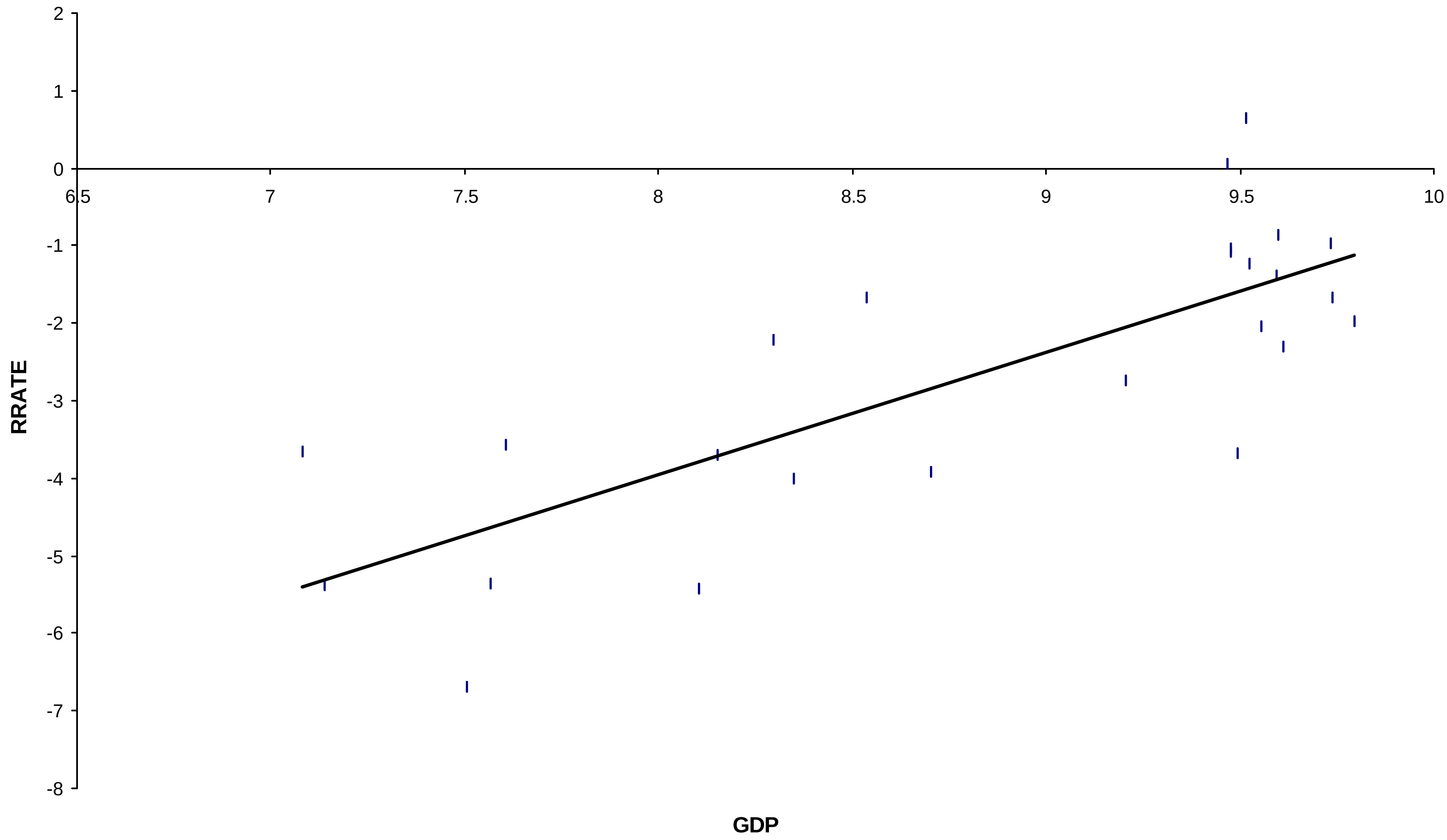

Figure 3 - RRATE(Contact Crimes) vs GDP