DOCUMENTO CEDE 2003-07
ISSN 1657-7191 (Edición Electrónica)
MARZO DE 2003

CEDE

WHAT PART OF THE INCOME DISTRIBUTION MATTERS FOR EXPLAINING PROPERTY CRIME? THE CASE OF COLOMBIA[1]

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Abstract

Inequality has always been taken as a major explanatory factor of the rate of crime. Yet, the evidence in favor of that hypothesis is weak. Pure cross-sectional analyses show significant positive effects but do not control for fixed effects. Time series and panel data point to a variety of results, but few turn out being significant. The hypothesis maintained in this paper is that it is a specific part of the distribution, rather than the overall distribution as summarized by conventional inequality measures, that is most likely to influence the rate of (property) crime in a given society. Using a simple theoretical model and panel data in 7 Colombian cities over a 20 year period, we design a method that permits identifying the precise segment of the population whose relative income best explains time changes in crime.

JEL Classification: C23, D3, D63, K42

Keywords: crime economics, income distribution, inequality

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[1] A previous version of this paper was presented at the Congress of the European Economic Association, Venice, August 2002

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1. Introduction

Inequality always ranked high among the potential economic determinants of property crime. The argument justifying this hypothesis is simple. Other things being equal, and in particular the probability of detection, the expected gain from crime may be taken as proportional to the mean income of the society under consideration, whereas the cost depends, through the opportunity cost of time or the punishment in case of detection, on the potential income of the would be criminal. Criminals in a society are thus likely to have a potential income at some distance below the mean income of society. It then follows that there will be more criminals the more people there will be at this relative income and below, or equivalently the more inequality there will be in society.

The empirical evidence on such a relationship between crime and inequality is mixed. In what probably was the first empirical paper on the economics of crime, Ehrlich (1973) found a significant relationship between the crime rate and the share of the population below half the median income across the US states. That cross-sectional relationship was more or less systematically confirmed by further work using different measures of inequality – see for instance Freeman (1996). Time series evidence is much weaker, however. Allen (1996) reports on several largely inconclusive studies of the aggregate crime rate in the US, whereas Freeman (1996) mentions that no significant effect was found in a cross-section of time series for various metropolitan areas in the US when controlling for fixed effects.[3] Cross-country evidence leads to analogous conclusions. Pure cross-country data reveal a significant positive relationship between crime rates and various inequality measures, whether one uses official crime rates collected by the UN – Loayza et al. (2001) – or data coming from victimization surveys. International panel data are difficult to put together because of comparability problems across countries and over time. Loayza et al. (2001) found the Gini coefficient not significant when using GMM on differenced time series, but they

[3] See also Entorf (2000) for Germany.

obtained a significant coefficient when using an Arellano-Bower system estimator.

An issue that should arise when trying to find some empirical support for the basic hypothesis of the crime-inequality literature is that of the representation of inequality one should use. Suppose that some redistribution takes place at the top of the distribution so that inequality in a given country diminishes. On the basis of the argument in the opening paragraph of this paper, should it be expected that the crime rate will come down, at least after some delay? Probably not if the redistribution is concerned with people high enough on the income scale not to be tempted by illegal activities. Thus, not any change in the distribution may cause a change in the crime rate and it is quite likely that using different inequality measures in regressions that try to explain the crime rate will lead to different results. The Gini coefficient might lead to a given result, but the Theil measure or the logarithmic deviation might lead to another one.

This remark has two implications. First, all empirical attempts at identifying some empirical relationship between crime and the distributional characteristics of a society should systematically rely on various summary inequality measures. Second, efforts should be made to identify what precise part of the distribution is actually relevant to explain differences in criminality across space and time.

This paper intends to shed some light on these two issues by studying the evolution of criminality over the last 15 years in the seven largest cities of Colombia. From the perspective of crime and inequality, Colombia appears as an interesting case study for several reasons. a) It is a high criminality country with rather large variations of the crime rate over time and across cities; b) the distribution of income has changed substantially during the period under analysis – 1985-2000 - with a first drop in inequality until 1990 and then a continuous

increase during the 1990s (Sánchez and Nuñez, 2001); c) besides inequality, guerilla and drug activities provide objective reasons for variation in the crime rate, even for property crime.

The paper is organized as follows. Section 2 shows the results from standard econometric analysis, the evolution of the crime rate on a cross-section of city time series. After controlling for fixed city and year effect, none of the variables used to explain changes in the crime rate turns out to be significant, except for income inequality when some specific summary measure is used. We then develop a theoretical model in section 3 which leads to an econometric structural specification of the way distributional characteristics should affect the crime rate, together with other crime determinants. Section 4 is devoted to the estimation of that model in the Colombian case and to the identification of that part of the distribution of income that turns out to be important for crime determination. According to our estimates, would be (property) criminals in Colombia are recruited in that part of the population whose standard of living lies below 80 per cent of the mean, that is practically the five or six bottom deciles. Interestingly enough, the other variables, which failed to be significant with the standard specification based on summary inequality measures, are significant when combined with the population and income share of the population that lies below the critical 80 per cent of the mean threshold. In summary, restricting the attention to that specific population considerably improves the quality of the empirical economic analysis of crime.

2. Cross-section time-series analysis of crime in the 7 largest cities of Colombia

In this section, we use standard techniques to analyze the determinants of crime in Colombia. The dependent variable is the annual rate of property crime per ***100 thousand*** inhabitant reported to the police in each of the 7 largest cities from 1986 to 1998. The corresponding time series are plotted in figure 1. It can be

seen there that the evolution of property crime has been rather different in the 7 cities with an increasing trend in Bogotá, fluctuations around a constant level in Medellin or Barranquilla, or a decreasing trend in Cali and Pasto.

Explanatory variables include four sets of variables. The first explanatory variable is the inequality of the distribution of income per capita in the city and during the year of observation. Data are from the household survey. Several summary inequality measures have been used. We report here only on the results obtained with the Gini coefficient, the Theil index, the mean logarithmic deviation and the Atkinson index with 5 different inequality aversion parameters. As mentioned above, the idea is to test whether the relationship between crime and inequality is sensitive to the representation that is given of the income distribution. Several definitions of the latter were also used, filtering the population by age or using the earnings of active workers rather than household income per capita. Overall, results were slightly better with all the population and income per capita – all households being weighted by their size.

A second set of explanatory variable summarizes the state of the labor market. This includes the rate of unemployment for people aged 17-25, the rate of labor force participation in the population at working age (15-65), and the real wage. The reason for using the rate of youth unemployment rather than total unemployment is the common belief that would be criminals are likely to be recruited among young people. The third set describes the urban environment. Two variables are being used. Total population size, which is supposed to represent variations in the density of metropolitan areas as well as migration movements, and the average schooling of the population at working age, again with the idea that important population movements may modify the educational structure of the population. It is expected that, other things being equal, crime increases with a positive variation in population size and a negative variation in mean education.

The fourth set of variables is more directly to crime. Given the specificity of Colombia, it seemed logical to include some controls for both drug business[4] and guerilla activity, both factors being conducive to more property crime by diverting police attention and providing model of violence. Police effectiveness is summarized by the number of homicides that actually led to some formal detention. The idea here is that homicides are the most serious crimes and failure by the police to do the proper arrests is an incentive for minor crimes.

Two additional sets of variables have been added to the regression for more technical reasons. On the one hand, a full set of city and year variables control for fixed effects due to unobserved permanent crime determinants at the city level or transitory crime determinants common to all cities. On the other hand, the lagged value of the crime rate is meant to account for some hysteresis of criminality – as theoretically justified for instance by Sah (1996). In general, it is difficult to combine cross-sectional heterogeneity and auto-regressive model specification. Hence the increasing use being made of Arellano-Bower GMM 'system' estimates in the cross-country literature. In the present case, using city dummy variables avoids the problem of the likely correlation between lagged effects and 'random' fixed effects.

Results shown in table 1 are rather poor. Practically, none of the explanatory variable is significant and the sign of coefficients often is the opposite of what is expected. It is interesting that these results are to a large extent related to fixed effects. Without fixed effects – both for years and cities - several variables turn out to be significant and with the expected sign. This is true of the inequality variables, in particular, which suggests that crime and inequality may be linked through a very long-run direct relationship that is visible essentially in the cross-

[4] It should be clarify that drug income are estimates and not observed data. The estimates are from Sanchez and Nuñez (2000)

sectional dimension, or simply through a simultaneous relationship with some unobserved fixed factor.

The second noticeable result in table 1 is the high variability of the results as a function of the inequality measure that is being used. Inequality is significant at the 10 per cent probability level when using the Gini coefficient but it is practically without any effect when using the Atkinson index with a high inequality aversion parameter. As a matter of fact, there seems to be a negative monotonic relationship between the quality of the regression and this inequality aversion parameter. Given the properties of the Atkinson index, this would suggest that it is not so much the relative income of the poorest that matters for crime but a more diffuse definition of inequality, a conclusion that seems to be in contradiction with basic intuition about crime determinants.

Marginal changes in the specification of the model – i.e. omission of some variables, use of arithmetic rather than logarithmic definitions, etc… - do not lead to different conclusions. Thus, the question arises of whether the linear specification of the regressions reported in table 1 and the representation of changes in the distribution through a single summary measure of inequality are an appropriate specification. It is shown in the rest of this paper that a more structural specification based on a simple economic model of crime yields much more satisfactory results. In particular, it permits identifying which part of the distribution really matters to explain variations in crime rates.

3. A structural econometric model of the crime rate

Following the argument in Bourguignon (2001), we assume that criminals are those people whose economic resources, y, are below a threshold that depends on the expected utility from crime. Let the latter be the expected loot, x, corrected by a term, α, that depends on the probability of being caught, p, the sanction, q,

if caught - expressed as a proportion of economic resources - and a set of variables summarizing the attitude of the individual and/or the social group he/she belongs to with respect to crime. To simplify let summarize all these variables by a single parameter, h, which we shall refer to as 'honesty'. We will assume that the statistical distribution of that attribute is defined on the support $[h_1, h_2]$ with density function *g( )*. To simplify, it is also assumed that honesty is distributed independently from economic resources.

Formalizing the previous argument, an individual with honesty h will get into crime if :

$$y \leq x.\alpha(p,q,h) \qquad (1)$$

The proportion of criminals among people with honesty h is therefore given by :

$$F[x.\alpha(p,q,h)]$$

where *F( )* is the cumulative function of the distribution of economic resources. Aggregating over all levels of honesty leads then to an overall proportion of criminals in the population, *C*, given by the following expression:

$$C = N.\int_{h_1}^{h_2} F[x.\alpha(p,q,h)]\,g(h)dh \qquad (2)$$

where N is the scale factor that stands for the number of crimes committed by a criminal, which is assumed here to be constant.

Let C_t be the crime rate observed at period *t (=1, 2, …T)* and let X_t be the vector of explanatory variables of the crime rate, excluding inequality summary measures. The standard econometric models of crime as well as the model used examined in the preceding section essentially relate the crime rate, C_t, to these variables X_t through a linear specification that also includes a summary measure, $G(F_t)$. The specification thus is : [5]

$$C_t = \beta_0 + X_t.\beta + \gamma.G(F_t) + u_t \qquad (3)$$

where β and γ are coefficients to be estimated and u_t is the usual error term.

There is no rigorous justification behind specification (3). The point is simply to identify variables that tend to covary with the crime rate and which might be considered as causes of crime. Yet, if one believes the microeconomic model (1) is a good representation of criminal behavior, then the adequate specification should be of type (2) rather than (3). To see what this implies, consider that the explanatory variables, X_t, may now be taken as the direct or indirect observed determinants of the expected utility of crime, $[x.\alpha(p, q, h)]_t$, conditionally on *h* at time *t*. Moreover, suppose that this dependency may be represented by the following linear equation:

$$[x.a(p, q, h)]_t = \bar{y}_t.[b_0 + bX_t + \mu_t + h] = \bar{y}_t.[b_0 + Z_t + h] \qquad (4)$$

In that expression, it is reasonably assumed that the net expected utility of crime is proportional to the mean income of the population, $\bar{y}_t$. The coefficient of proportionality, which will be called the 'propensity to crime', is supposed to

[5] For estimation of models of type (3) see the rich list of references in Gartner (2000).

depend linearly on observed determinants of crime, X_t, the honesty parameter, h, and a set of unobserved determinants the effect of which is summarized by μ_t. b_0 and b are coefficients to be estimated and there are the analogous of β_0 and β in the standard model (3).[6] The last equation defines the propensity to crime as made up of three parts: a constant, a common time varying term, Z_t, and the honesty parameter, h. The common propensity to crime variable, Z_t, will be important below.

Substituting now (4) into (2) leads to :

$$C_t = N.\int_{h_1}^{h_2} \overline{F}_t\left(b_0 + X_t b + \mu_t + h\right) g(h)\, dh \qquad (5)$$

where $\overline{F}_t()$ now stands for the distribution of income normalized by the mean, or the distribution of relative incomes at time t. Under the assumption that the time variations of $X_t b + \mu_t$ are relatively small, one may use a linear approximation of the preceding expression :

$$C_t / N \cong \int_{h_1}^{h_2} \overline{F}_t\left(b_0 + h\right) g(h)\, dh + \left[X_t b + \mu_t\right] \int_{h_1}^{h_2} \overline{f}_t\left(b_0 + h\right) g(h) dh \qquad (6)$$

where $\bar{f}_t()$ stands for the density of the relative income distribution at time t.

It now remains to make an assumption on the distribution of the honesty parameter, h, within the population. Without any information available, this

[6] There is no need to affect a coefficient to the honesty parameter h, since its scale has been left unspecified.

assumption is necessarily arbitrary. For the sake of simplicity, it is assumed in what flows that *h* is uniformly distributed over the interval $[h_1, h_2]$.[7] Under that assumption, it is easily shown that (6) becomes :

$$C_t / N \cong \phi_t(b_0, h_1, h_2) + \psi_t(b_o, h_1, h_2)\left[X_t b + \mu_t\right] \tag{7}$$

$$\phi_t(b_0, h_1, h_2) = \overline{F}_t(b_0 + h_2) - \psi_t\left[\overline{Y}_t(b_0 + h_1, b_0 + h_2) - (b_0 + h_1)\right] \tag{8}$$

$$\psi_t(b_0, h_1, h_2) = \frac{\overline{F}_t(b_0 + h_2) - \overline{F}_t(b_0 + h_1)}{h_2 - h_1} \tag{9}$$

where $\overline{Y}_t(u, v)$ stands for the mean relative income of all people whose income is between u and v time the mean at time t.

The first term of (7) may be interpreted as a measure of inequality of the distribution of income for people whose income lies in the interval $[b_0 + h_1, b_0 + h_2]$. In effect, the function $\varphi_t(\ )$ term combines various types of information on the shape of the Lorenz curve in that interval : how many people are they, and how poor are they in comparison with the mean income. That this function measures something that resembles inequality is made clear with the observation that it increases when the proportion of people below the relative income limit, b_0+h_2, increases or when the mean relative income of people in the interval $[b_0 + h_1, b_0+h_2]$ goes down. With this remark, specification (7) becomes very similar to the standard model. The crime rate depends linearly on some measure of inequality and on the explanatory variables, X_t.

[7] Yet, other distributional assumptions are possible. They would lead to much more complicate numerical calculations, though.

There is a big difference between specifications (3) and (7), though. It is that the effect of the explanatory variables, X_t, on the crime rate in the latter is *filtered by a term that depends on the distribution of income at time t*. This term, $\psi_t(\ )$, is the average density of the distribution within the interval $[b_0+ h_1, b_0+h_2]$. In other words, the major difference between the reduced form model (3) and the structural model (7) is that *crime determinants affect the crime rate more or less depending on the number of people who lies in an income range low enough to make them potential criminals*. Unlike (3), specification (7) allows for some interaction between the distribution of income, $F_t(\ )$, and the explanatory variables, $X_t(\ )$. But the shape of that interaction has a very specific structure that would probably not be captured by simply adding some cross-products between X_t and $G(F_t)$ in (3).

That structure essentially depends on the two parameters, h_1 and h_2, the role of which is essentially to define what part of the distribution of income really matters for explaining variations in the crime rate. This was the question to which pointed the standard empirical analysis undertaken in the previous section of this paper. We intend to answer it now by estimating econometrically those two parameters, as well as the coefficients, b, that represent the way the explanatory variables, X, affect criminal behavior.

4. Estimation procedure and results

In this final section, we estimate model (7) on the cross-section of the 7 largest Colombian cities between 1986 and 1998. The model to be estimated is highly non-linear. What is more problematic is the fact that the evaluation of the functions $\varphi_t(\ )$ and $\psi_t(\ )$ for given values of $b_0+ h_1$ and b_0+h_2 requires using the full sample of households for each observation of a city i at a period t. This difficulty was met by estimating the whole model for fixed $b_0+ h_1$ and b_0+h_2 and iterating over those two parameters, so as to minimize the sum of square residuals.

To be more precise, let us first add the city index i to all the observations t. Then, define the common propensity to crime, $Z_{it,}$ in city i at time t so as to introduce some hysteresis in that behavior :

$$Z_{i,t} = \rho Z_{i,t-1} + b.X_{i,t} + \varepsilon_{i,t} \qquad (10)$$

The argument that led to (7) is still valid. For given N, $b_0 + h_1$ and $b_0 + h_2$, Z_{it} is obtained through the following simple transformation of the observed crime rate, C_{it}:

$$Z_{it} = \frac{C_{it} / N - \phi_{it}(b_0, h_1, h_2)}{\psi_{it}(b_0, h_1, h_2)} \qquad (11)$$

where $\varphi_{it}(\ )$ and $\psi_{it}(\ )$ are given by (8) and (9). Of course, this specification relies on the implicit assumption that the distribution of the honesty parameter is the same across cities and time periods.

Estimates of ρ, b, b_0, N, h_1, h_2, may be obtained by minimum least squares. Here this method consists of minimizing the sum squared residuals corresponding to equation (10). This is done by estimating ρ, b_0 and b by OLS on a grid of values for N, $b_0 + h_1$ and $b_0 + h_2$ in (11) and then choosing the combination ($b_0 + h_1$, $b_0 + h_2$) that minimizes the sum of squared residuals in (10).[8]

As in the standard model estimated above in section 2, fixed effects are added in (10) for both cities and years. The value of b_0 could be obtained by averaging all

[8] Under usual normality assumptions on the random terms, ε_{it}, this is equivalent to the maximum likelihood estimator.

these fixed effects and then one it would be easy to derive the values of h_1 and h_2. But, of course, only the bounds of the relative income range where distribution, that is b_0+ h_1 and b_0+h_2, matter. Only those two parameters, the full vector of coefficients, b, and the auto-regressive coefficient, ρ, are reported in the table below. In effect, iterating on N, it turned out that an order of magnitude of 10 was given the best results. This value was kept in the all the subsequent estimation work.

Figure 2 shows the sum of squared residuals obtained for combinations of values of (b_0+ h_1, b_0+h_2). Of course, only that part of the space where $h_1<h_2$ is of relevance here. It can be seen on that figure that the sum of squared residuals is minimized for an upper limit b_0+h_2 equal to .8 and a lower limit, b_0+ h_1, equal to 0. But, really, there is practically no difference between a lower limit at 0 or at .2 or even .3, this reflecting the very low density close to zero income per capita. According to these results, that part of the population which matters for time fluctuations in the crime rate thus, are those individuals whose welfare is below 80 per cent of the mean of the whole population. It is the proportion of people, their mean relative income and the average density of the distribution in that relative income range that better explains time variations in the crime rate across cities. On average over all observations, approximately 60 per cent of the population is in that relative income range.

Table 2 shows the OLS estimates of the coefficients in equation (10) obtained after transforming the crime rate by equation (11), the functions $\varphi_{it}(\ )$ and $\psi_{it}(\ )$ thus being computed on the basis of the preceding bounds of the relative income range (b_0+ h_1, b_0+h_2). The variance of the estimates is that of OLS. Actually, it tends to under-estimate the actual variance because the imprecision coming from the estimates of (b_0+ h_1, b_0+h_2) is not taken into account.[9] But this

[9] A more rigorous estimation of this covariance matrix could be obtained by using standard maximum likelihood techniques.

bias is ignored in what follows because this makes the comparison with the results of the standard model easier.

Because of the transformation made on the dependent variable, it is not possible to do simple comparison tests between the present regression on 'transformed' crime rates and the standard model discussed in section 2. Yet, casual comparison of tables 1 and 2 shows a great superiority of the model run on the transformed crime rate. If it were within a linear setting, the jump from 72 to 83 per cent of the R^2 statistic would be the proof of a major improvement. Many of the estimated coefficient now are statistically significant – conditionally on the value of the parameters (b_0+ h_1, b_0+h_2)- whereas this was the case for none of them with the standard specification. Finally, most of them have the expected sign and order of magnitude. Again, this was seldom the case before.

Going down the list of explanatory variables, let us discuss first the estimates obtained for the labor-market variables. The youth unemployment rate has the expected positive and significant effect on the crime rate. Note that the coefficient reported in table 2 over-estimates the true quasi-elasticity of the crime rate, because the dependent variable is not the logarithm of the crime rate itself but of the crime rate *minus* the variable $\varphi_{it}(\ )$. As the latter is positive, the quasi-elasticity of the crime rate with respect to youth unemployment is actually smaller than the reported coefficient. The effect of the participation rate is more or less the opposite of the effect of unemployment, although just below the limit of statistical significance. To the extent that variations in this participation rate may account for changes in disguised unemployment, this could be expected. Finally, the (log) real wage is estimated to have a positive effect on crime. Although not statistically significant, this effect is somewhat surprising since one would have expected a priori that any evolution favorable to labor in general would reduce crime. However, it must be taken into account that the change in the real wage must be interpreted at constant unemployment and participation

rates, as well as at constant distribution of income among the poorest 60 per cent. Another possible interpretation is that a change in the real wage increases the potential loot of property crime by more than the average income, because wage workers are predominantly in the top 40 per cent of the distribution.

As far as general population variables are concerned, it turns out that fluctuations in population size[10] have no significant impact on crime whereas those in the mean schooling of the working age population is almost significant and positive– recall that the effects of the long-run common trend in urban population and its mean schooling are accounted for by the year dummies included in the regression. Unlike what might have been expected, these results suggest that migration movements which may be responsible for deviations of population growth from trend have no impact on crime. In theory, this should be the case only if crime prevention and police expenditures were growing at the same rate as population. Unfortunately, the information available in this respect is extremely partial and, as will seen below, not necessarily consistent. With respect to the positive effect of mean schooling, one possible interpretation is that, after controlling for changes in the size of the population, changes in that variable correspond to changes in the demographic structure of the population[11]. As age is probably the characteristic most directly linked to schooling, this variable might show the effect on crime of the population becoming younger or older in a way that departs from the trend common to all cities.

Two out of the three crime environment variables are significant and have the expected sign. Other things being the same, drug activity[12] in the city and guerilla activity in the region may be supposed to divert police attention from other criminals, which should increase the propensity to commit property crime. This is

[10] The population is the inter census projected population and it does not contain of course its year to year fluctuations.
[11] Schooling has two opposite effects on crime: raises opportunity cost and increases wealth.
[12] Again, it has to opposite effect. It may attract property criminals to drug trafficking lowering property crime or it may divert police to other activities.

what is observed. More problematic is the positive and almost significant sign obtained for the homicide detection rate. This variable was supposed to be a proxy for the level of police activity relatively to the number of homicides.[13] The positive sign obtained in the regression seems to imply some kind of crowding-out of property crime detection by arrests for homicides –i.e. the same diversion phenomenon that is behind the guerilla and drug coefficients. Of course, it would be much better to use directly the size of the police force or expenditures on police as an explanatory variable. Unfortunately, this information is not available for the whole period under analysis.

The last variable in the list is the lagged (log) transformed crime rate. The coefficient is positive and significant. It suggests some sizable hysteresis of changes in the crime rate. According to that coefficient, 30 per cent of a shock in the crime rate at a point of time is carried over to the next year. This also implies that long-run changes in the crime rate associated with permanent changes in the explanatory variables are higher than the coefficients reported in table 2 by approximately 40 per cent.

Conclusion

This paper investigated a structural specification of an econometric model of the crime rate in the 7 largest cities in Colombia that takes into account the simple fact that only a specific part of the income distribution should matter in determining the aggregate crime rate in a society. This specification led to the conclusion that would be criminals in Colombia were to be found among those people living in households where income per capita was below 80 per cent of the mean. A corollary of this is that distributional changes among those people above that limit are likely to have no significant influence on the crime rate.

[13] Assuming that the number of arrests for homicides, A, depends on the number, H, of homicides and the size, P, of the police force through the following simple 'production' function : $A = H^m P^{1-m}$. Then the detection rate A/H is given by $(P/H)^{1-m}$.

Interestingly enough, it turns out that this structural specification leads to an overall explanation that appears better then that of the standard model where the crime rate is simply regressed on some summary inequality measures and several supposedly relevant explanatory variables. This is true in terms of both the precision of the coefficients of these variables and the interpretation to be given to them.

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^Table 1. Regression results on panel crime rate data according to summary inequality measure being used[a]

Dependent variable is the log of crime rate

Inequality measure being used	Gini	Theil	Mean logarithmic deviation	Atkinson(.5)	Atkinson (1)	Atkinson(2)	Atkinson(3)
Inequality variable	4.076	0.858	1.811	3.893	2.818	1.801	0.391
	1.821	*1.527*	*1.538*	*1.749*	*1.552*	*1.121*	*0.381*
Other explanatory variables							
Youth unemployment rate	-2.316	-2.139	-2.233	-2.410	-2.182	-2.277	-1.964
	-0.732	*-0.675*	*-0.702*	*-0.762*	*-0.685*	*-0.709*	*-0.604*
Participation rate	-0.632	-0.657	-0.631	-0.549	-0.656	-0.177	-0.353
	-0.151	*-0.157*	*-0.149*	*0.131*	*-0.155*	*-0.042*	*-0.311*
Log real wage	-0.791	-0.723	-0.697	-0.813	-0.705	-0.497	-0.207
	-0.910	*-0.818*	*-0.794*	*-0.925*	*-0.802*	*-0.573*	*-0.248*
Log population	-4.439	4.630	-4.330	-4.511	-4.292	-4.076	-4.399
	-1.717	*-1.800*	*-1.665*	*-1.752*	*-1.650*	*-1.554*	*-1.683*
Log mean schooling	-1.859	-1.700	-1.806	-1.811	-1.804	-1.771	-1.591
	-1.003	*-0.929*	*-0.971*	*-0.982*	*-0.970*	*-0.946*	*-0.853*
Log homicide detection rate	0.123	0.130	0.131	0.130	0.127	0.124	0.132
	0.853	*-0.929*	*0.910*	*0.905*	*0.880*	*0.853*	*0.911*
Guerilla activity (dummy)	-0.002	-0.002	-0.002	-0.002	-0.002	-0.001	-0.001
	-0.563	*-0.702*	*-0.550*	*-0.610*	*-0.544*	*-0.410*	*-0.311*
Log drug income per inhabitant	-0.358	-0.412	-0.387	-0.389	-0.379	-0.378	-0.381
	-0.857	*-1.012*	*-0.932*	*-0.941*	*-0.911*	*-0.908*	*-0.931*
Lagged Log crime rate	0.129	0.147	0.140	0.134	0.139	0.145	0.170
	0.936	*1.074*	*1.011*	*0.975*	*0.139*	*1.020*	*1.177*
R^2	0.720	0.710	0.714	0.717	0.715	0.708	0.699
Mean square error	0.201	0.208	0.204	0.203	0.204	0.209	0.215
Number of observations	84	84	84	84	84	84	84

Table 2. Regression results on panel crime rate : transformed crime rates [a]

Dependent variable is the log of transformed crime rate (b0+h1= .0; b0+h2=.8)

Explanatory variables	Coefficients	Standard error	T-statistic
Youth unemployment rate	7.959	2.65	3.00
Participation rate	-5.688	3.53	-1.61
Log real wage	1.064	0.67	1.58
Log population	-2.215	3.15	-0.70
Log mean schooling	2.985	1.59	1.88
Log homicide detection rate	0.257	0.15	1.77
Guerilla activity (dummy)	0.008	0.00	2.97
Log drug income per inhabitant	1.224	0.40	3.02
Lagged Log (transformed) crime rate	0.313	0.15	2.15
R^2		0.831	
Mean square error		0.134	
Number of observations		84	

[a] See estimation method in text. Coefficient of dummies for cities and years not reported.

Figure 1a. Crime rates in Colombia's 4 largest cities

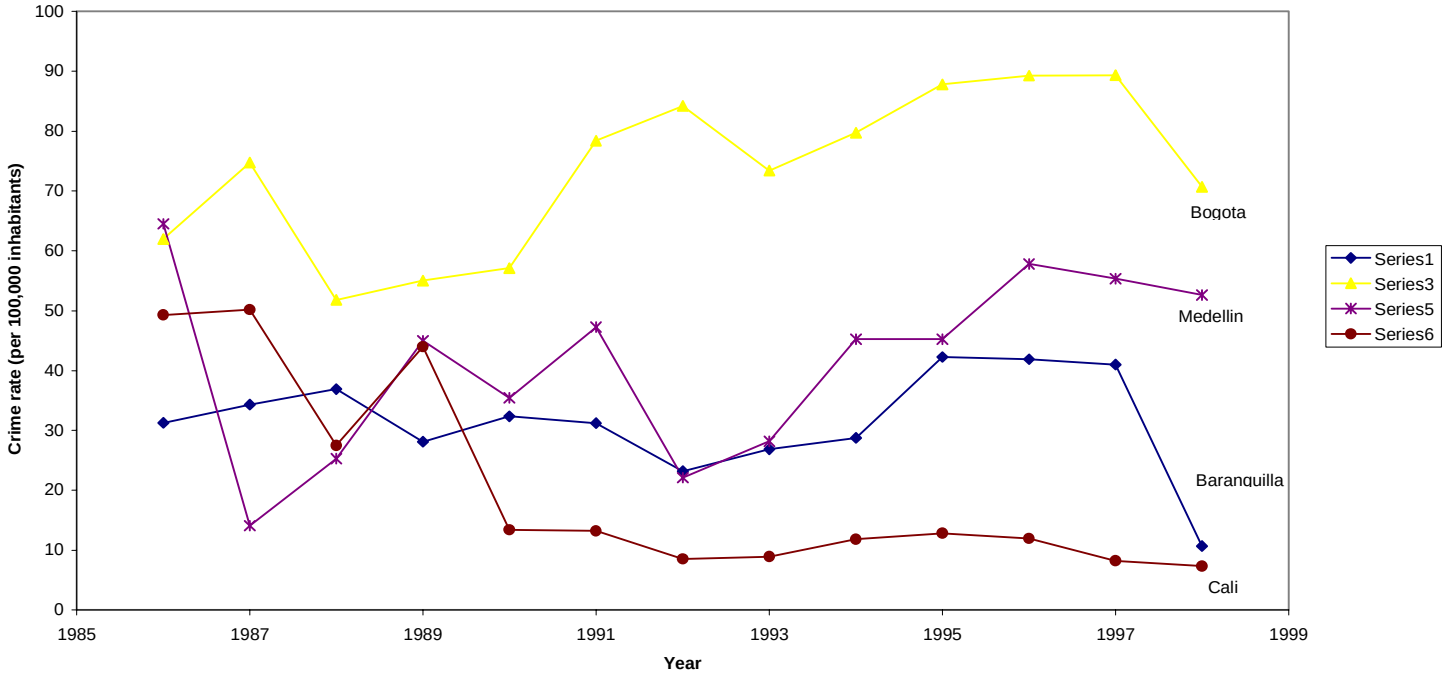

Figure 1b. Crime rates in Colombia's 7 largest cities

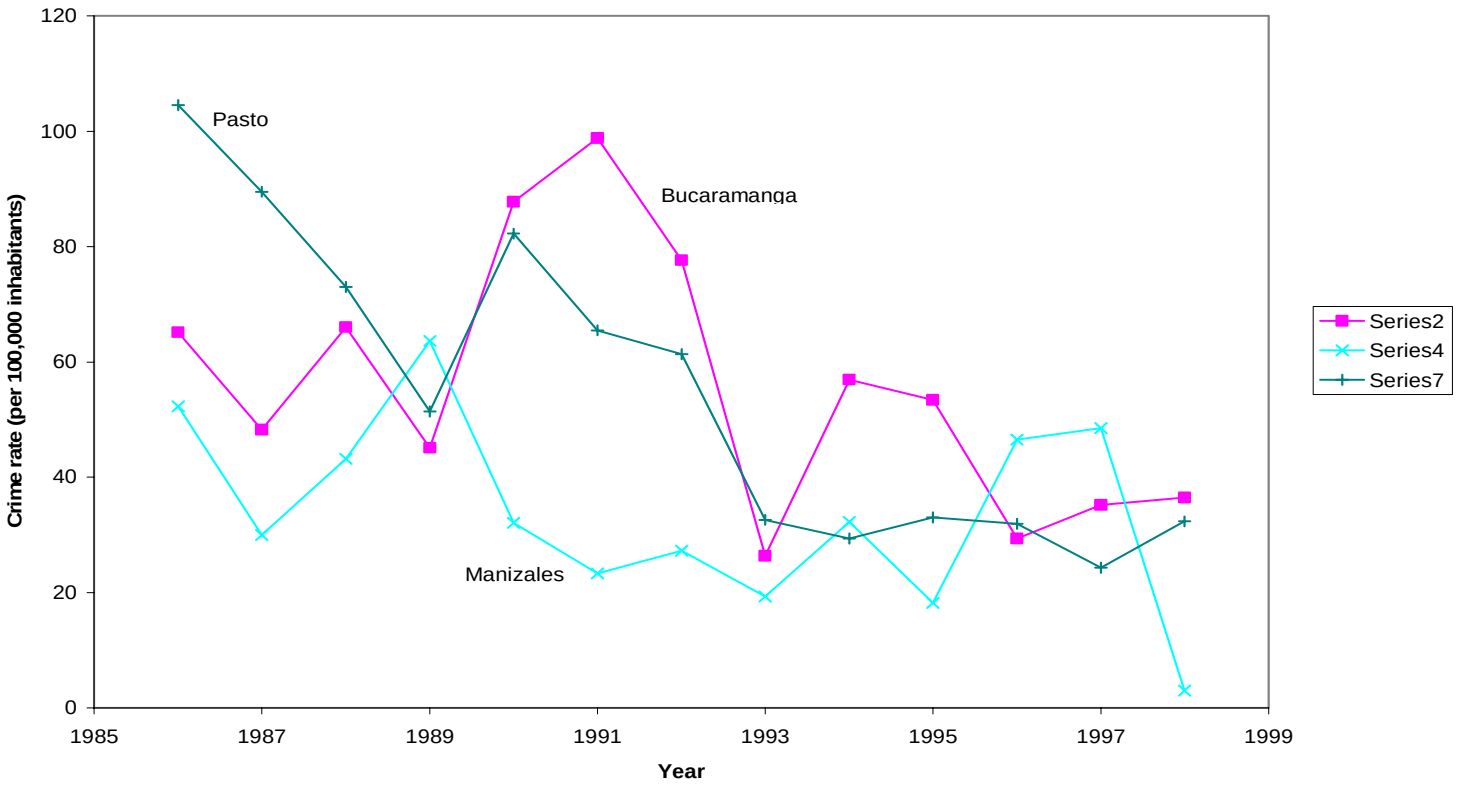

Figure 2. Sample likelihood conditionally on lower, b0+ h1, and upper,b0 + h2, limits