Socio-Economic Development and Violence: An Empirical Application for Seven Metropolitan Areas in Colombia

Alexander Cotte Poveda

*University of Göttingen and University of La Salle, alexcotte@yahoo.com

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Abstract

This work uses several empirical approaches to examine the effects of poverty and inequality on violence in the seven metropolitan areas in Colombia. To this end, this study describes the main determinants of violence in these cities; these determinants are all fundamental features of social instability. For this description, this paper uses several econometric approximations to compare and determine an adequate estimator for the analysis of Colombian urban violence. This hypothesis was supported by evidence showing that factors related to poverty, inequality, and education directly influenced violence in the cities. Because of their effects over time and their incidence rates across society, these factors also had negative effects on the economic and social development of every city analysed.

KEYWORDS: poverty, inequality, economic development, growth, socio-political instability, violence, panel data

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1. Introduction

Studies of the determinants of socio-economic violence in the recent literature show that violence and instability may influence economic activity and development. Moreover, several investigations have discussed the factors that cause violence, suggesting that these factors may have a direct relationship with increases in poverty, income inequality and social development (Brush, 2007, Cotte, 2010). In this respect, recent evidence has demonstrated that the deficiencies observed in human capital, infrastructure and environmental conditions as well as social, economic, cultural and political structural characteristics of a society are factors that influence violence and criminality in cities (Ergun et al., 2003). This paper aims to analyse the varying effects of inequality and poverty on violence between 1984 and 2006 in the seven metropolitan areas in Colombia.

Cross-sectional studies have found a positive association between inequality and crime. Urban violence may be the result of development dynamics that differ across counties (Parsley, 2001). Nonetheless, everywhere violence is generated by a variety of causes. Evidence has confirmed that existing economic, social and political conditions help determine whether a country is prone to violence. Specifically, the institutional structure of a society, including features and elements that may generate urban violence, determines the incentives of agents with respect to economic decisions.

The motivation to study this topic emerges from the sharp increase in the average rate and in the number of homicides in Colombia over the last few decades and from the differences in the homicide rates among the seven metropolitan areas in Colombia. The preliminary data analysis suggests stable homicide rates across several cities despite the variability in the national average. Regardless of whether the geographic distribution of homicide rates has significantly changed, the sharp rise in the average homicide rates in the cities investigated in the study may be analysed through the cyclical and dynamic relationships that generally affect economic factors, which include unemployment, economic growth, inflation, education, inequality and poverty.

Against this backdrop, the present study seeks to explain the importance of socio-economic determinants of violence, particularly the impact of human capital, poverty, inequality and variables of market labour, in seven metropolitan areas in Colombia. To the best of our knowledge, no other studies have explicitly applied several econometric approximations to compare and determine an adequate estimator in the analysis of Colombian urban violence.

This research aims to use different empirical approaches to describe the trends in poverty, inequality, and economic development in the seven Colombian cities and to show how these trends have influenced urban violence. With this
goal in mind, quarterly data from the seven Colombian cities were analysed using several econometric panel data models with unbalanced data for the period 1984-2006. In this study, various types of estimates were applied to control for the heterogeneity problem as well as for the heteroskedasticity problem or cross-sectional dependence in the estimations with fixed effects that emerged across the cities.

In this study, a fixed-effect model helps solve the endogeneity problem because this model allows us to control for various unobservable influences on homicide rates across cities and over time (Däubler, 2006, Hanchane and Mostafa, 2010). Moreover, the time fixed effects test determines that no time fixed effects are needed, whereas entities fixed effects are required according to the respective tests. Therefore, by implication, the fixed-effect model helps solve the endogeneity problem by controlling for city-specific and time-independent unobservable influences in Colombian cities.

Other empirical research has analysed the aspects associated with violence and instability in the comparisons across countries and over time. However, few empirical studies have investigated the trends of violent behaviour and instability in urban areas. This research seeks to contribute to the existing literature by analysing the particular case of Colombian cities using various approaches and empirical models.

In this context, in order to understand the effects that phenomena, such as poverty, inequality, education, development, and socio-economic factors, have on violence, this paper suggests a particular analysis that is different from other conventional approaches that have studied this topic in cities. The rest of the paper is organised as follows. Section 2 reviews the literature. Section 3 describes the data and methods used in this study. Section 4 presents the main findings and analyses the results, and Section 5 concludes.

2. Literature Review

It is widely accepted that factors, such as inequality, poverty, and human capital, directly influence urban violence, generating negative effects on the economic and social development of a country or city in general. Indeed, various studies have evaluated these effects using various qualitative and quantitative approaches. Jong (2009) suggested that political instability has four manifestations: (I) politically-motivated violence, (II) mass civil protest, (III) instability within the political regime, and (IV) instability of the political regime; each manifestation exerts several effects on economic growth. Other authors have studied the empirical correlations and theoretical linkages between political instability and economic
growth, demonstrating the negative and significant relationship between these variables (Cotte, 2007, Darby et al., 2004, Ades and Chua, 1997).

Another important factor that impacts crime trends is the criminal laws. Economic theories illustrated by Becker (1968) have shown that criminals participate in illegal activities if the expected benefit of those illegal activities exceeds the expected benefit of legal activities. Several studies have demonstrated that adequate legislation could reduce violence and crime rates by increasing the expected consequences for crime or violence, as criminals would expect greater risks of injury and lower rates of success in carrying out criminal activities (Lott and Mustard, 1997, Lott, 2000, Kovandzic et al., 2005).

Various studies in developing countries with long traditions of violence have demonstrated low socio-economic status, perhaps as a consequence of the violence, which may have taken human lives, destroyed economic assets, or prevented the accumulation of capital and wealth thus generating insecurity and instability (Cotte, 2011a). This instability could, in turn, undermine long-term economic growth and development (Adler et al., 2010, Collier, 2007). Buscaglia (2008) applied an empirical model and found that the operational presence of the government is fundamental to increasing development and security in countries. Areas with high unemployment and poverty show a higher risk of organised crime. Caruso and Schneider (2011a) used several econometric techniques in their investigation of the socio-economic causes of terrorism and political violence in Western Europe. In these countries, they confirmed the classical economic argument that states that individuals with lower or fewer economic opportunities are more likely to be involved in terrorism activities. Caruso and Schneider (2011b) also analysed al Qaeda-style terrorist activities using a panel data model. This study demonstrated that terrorist activities are closely correlate with socio-economic conditions of populations and with the strength (or weakness) of the presence of government.

Goglio (2010) identified the effect on the long-term competitiveness of local areas or cities, particularly on non-material production factors, such as human capital, social capital and entrepreneurship, as a substantial harmful impact of crime. This effect is especially severe where organised crime exerts control over a given territory and influences its patterns of development, displacing the state presence. This effect then generates instability and helps to increase violence and criminal activity. Sun et al. (2011) used multivariate regression analyses to determine the effects of economic deprivation on crime and found that income inequality is a significant predictor of violence. Therefore, economic deprivation mediates the effect of social change on crime.

Detotto and Otranto (2010) investigated the macroeconomic consequences of criminal activity through empirical analysis and found that crime negatively affects economic performance in a number of ways, including discouraging
investment, reducing the competitiveness of firms, and reallocating resources creating uncertainty and inefficiency. Additionally, the study suggested the presence of a cyclical component, strictly related to the economic business cycle, in the effects of crime.

Soares (2004) evaluated the causes of heterogeneity in crime rates across countries, suggesting that declines in inequality and increases in growth and education are linked to reductions in crime rates. Furthermore, in the context of violence in Indonesia, Tadjoeddin and Murshed (2007) determined that strengthening human development at an early stage has a strong violence-reducing impact.

In the context of Colombia, studies have focused specifically on the analysis of inequality and the index of quality of life, concluding that inequality and poverty may partially explain the increase of violence over the last decade (Cotte, 2011b, Gutierrez and Gallo, 2002, Valenzuela, 2002, Rubio, 2000, Sarmiento, 1999). Bourguignon et al. (2002) studied the effects of income distribution on crime using fixed-effects data and demonstrated that only a specific part of income distribution impacts crime trends in Colombian cities. Furthermore, other studies have shown that the effect of volatility on economic growth in the last decade has negatively affected the most vulnerable populations, which has led to a deterioration of major social indicators, such as poverty and social welfare, and caused a low rate of economic growth (CGR and CID, 2004, Garay, 2002).

Taking into account these recent studies, we limit our investigation of the relationship of poverty, inequality and education with urban violence in cities to the case of Colombia. Using several empirical models, this paper seeks to analyse and describe the main determinants of violence in seven metropolitan areas in Colombia and the determinants’ relationship to social instability. The following hypothesis is the basis of this study: the socioeconomic well-being of cities is shaped by the interaction between inequality and the increase in political and social instability. Therefore, high inequality and social exclusion, produced by the lack of opportunities and the access to quality basic services, labour markets and education, undermine social cohesion and increase poverty, which generates greater levels of urban violence.

3. Empirical Strategy and Model Specification

3.1 Data and Stylised Facts

Data were clustered quarterly for the period 1984-2006 for seven Colombian cities: Barranquilla, Bogotá, Bucaramanga, Cali, Medellín, Manizales and Pasto.
The dependent variable was homicide rates by city. The following main data sources were used: the National Institute of Legal Medicine, the National Policy of Colombia Thought Centre of Criminalist Research (DIJIN) (Centro de Investigaciones Criminológicas, DIJIN), the information systems SIEDCO (Sistema Estadístico Delincuencial, Contravencional y Operativo) and CERAC (Conflict Analysis Resource Center), the DNP (National Planning Department) and the DANE (Colombian Department of Statistics).

The following explanatory variables were calculated from the National Survey of Households DANE (Colombian Department of Statistics), the Colombian education ministry, the DNP (National Planning Department), and the Colombian treasury ministry: (I) the secondary education coverage of the population by city; (II) primary education coverage by city; (III) the GINI index by city; (IV) the indigence index by city; (V) poverty indicators by city; and (VI) salaries by city (for more details see appendix 1). Following the recent literature on this subject, the model included various social indicators by city with the aim of testing the socio-economic development level of each city. When the development level was calculated for each city, the effects of inequality, poverty and human capital on violence became evident.

The homicide rates in Latin American and Caribbean countries in the last year were high. For example, in 2010, the homicide rates per 100,000 people for the countries with the six highest homicide rates were as follows: Salvador, 61; Venezuela, 48; Colombia, 37.3; Belize, 32.7; Jamaica, 32.4; and Brazil, 25.3. In 2008, the countries with the five highest homicide rates were as follows: Honduras, 60.9; Jamaica, 59.5; Venezuela, 52; Salvador, 51.8; and Colombia, 38.8. The homicide rate in Colombia, in 2008, was 7.4 times that of other Latin American countries, such as Argentina, 5.2 and Uruguay, 5.8; 23 times that of Canada, 1.7; and, on average, 48 times that of Germany, 0.8, Switzerland, 0.7, Spain, 0.9, and Sweden, 0.9 (UNODC, 2010).

Table 1 Summary Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Homicide Rate</td>
<td>15.955</td>
<td>10.172</td>
<td>2.758</td>
<td>69.761</td>
</tr>
<tr>
<td>Secondary education coverage</td>
<td>0.783</td>
<td>0.271</td>
<td>0.021</td>
<td>1.160</td>
</tr>
<tr>
<td>Primary education coverage</td>
<td>1.100</td>
<td>0.224</td>
<td>0.053</td>
<td>1.609</td>
</tr>
<tr>
<td>Prices</td>
<td>0.689</td>
<td>0.550</td>
<td>0.044</td>
<td>1.764</td>
</tr>
<tr>
<td>Poverty</td>
<td>58.683</td>
<td>7.148</td>
<td>32.51</td>
<td>80.59</td>
</tr>
<tr>
<td>Indigence</td>
<td>0.2246</td>
<td>0.068</td>
<td>0.071</td>
<td>0.499</td>
</tr>
<tr>
<td>Unsatisfied Basic Needs</td>
<td>20.147</td>
<td>5.817</td>
<td>11.53</td>
<td>36.60</td>
</tr>
<tr>
<td>GINI</td>
<td>0.429</td>
<td>0.041</td>
<td>0.322</td>
<td>0.538</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>0.136</td>
<td>0.036</td>
<td>0.049</td>
<td>0.230</td>
</tr>
<tr>
<td>Real Salaries</td>
<td>379511</td>
<td>65377</td>
<td>243140</td>
<td>633128</td>
</tr>
<tr>
<td>Employments Level per Industry</td>
<td>67.860</td>
<td>20.903</td>
<td>28.6557</td>
<td>126.084</td>
</tr>
</tbody>
</table>
The homicide rate is extremely high in several Latin American cities. In fact, several of these cities had the highest homicide rates in the world in 2009. For example, the first position is occupied by Ciudad Juarez (Mexico), which had the highest rate with 191 homicides per 100,000 habitants followed by San Pedro Sula (Honduras) with 119, San Salvador (El Salvador) with 95, Caracas (Venezuela) with 94, Guatemala (Guatemala) with 86, Cali (Colombia) with 73, Tegucigalpa (Honduras) with 69, New Orleans (USA) with 69, Medellin (Colombia) with 62 and Cape Town (South Africa) with 60 (SJP, 2010). Various studies have indicated that these trends are mainly the result of poverty, inequality and drug trafficking that has undermined the economic growth and development of these cities over time. These facts demonstrate the importance of the analysis of urban violence in Colombia to determine the causes of such trends in order to aid in the development of adequate policies and strategies to lead to greater economic growth and development, security and social stability in the long run.

3.2 Model Specification

We used the data to build an unbalanced panel for seven metropolitan areas in Colombia over a period of 23 years (1984-2006), generating a total of 623 observations. Some studies have demonstrated that the use of the ordinary least square approach (OLS) for panel data is not optimal for the following reasons: (I) because panel data results in repeated observations for each unit of analysis, there may be unit-specific and time-specific features in the data and (II) there is a high possibility that the error process is not spherical because of heterogeneity among the units of analysis, correlations among the error terms of the same units of observation (serial correlation) and correlation among different units of observation (contemporaneous correlation). From this evidence, our analysis considered heteroskedasticity and serial auto-correlation problems through the application of the generalised least square (GLS) technique.

However, the problem with this technique is that the covariance matrix of any errors is assumed to be known at least up to a scale factor that is never known in practice. Feasible generalised least square (FGLS) has become the more commonly used technique. Parks (1967) applied FGLS to time-series cross-section (TSCS) models with panel errors. The following are three important criticisms of FGLS estimators: (I) FGLS fits well in large samples, but the finite sample properties of an FGLS estimator are difficult to perform; (II) FGLS standard errors undervalue true variability at least for normal errors; and (III) FGLS may not be adequate if a panel’s time dimension is smaller than its cross-sectional dimension.
Beck and Katz (1995) have proposed relying on OLS coefficient estimates with corrected standard errors (PCSE), which account for heteroskedasticity, serial autocorrelation and contemporaneous correlation. A criticism against this method suggested by Beck and Katz (1995) is that although the standard errors are established on T-asymptotics, the small sample features of PCSE estimators are poor when the panel’s cross-sectional dimension is large in comparison with the time dimension.

Relying on large T-asymptotics, Driscoll and Kraay (1998) have shown that the standard non-parametric time series covariance matrix estimator can be changed so that it remains robust when assessing very general forms of cross-sectional and temporal dependence. In their methods, they adjusted the standard errors using a Newey-West type correction to the sequence of cross sectional moment conditions, which ensures that the covariance matrix estimator is consistent, independent of cross sectional dimension, according to Hoechle (2007). Therefore, Driscoll and Kraay (1998) reduced the deficiencies of time-consistent covariance matrix estimators, such as the Parks-Kmenta method or the PCSE approach, which typically become inadequate when the cross-sectional dimension of a micro econometric panel is large.

The Driscoll-Kraay (1998) method is also applicable in cases using the fixed-effect model. As we dealt with panel data, we believed that there were city-specific and time-specific effects. Therefore, instead of relying on OLS coefficients, we relied on the fixed effects estimator of Driscoll and Kraay (1998), which accounts for the problems of panel heteroskedasticity and serial autocorrelation. The tests applied for estimated residuals to fixed-effect models showed heteroskedasticity and cross-sectional dependence problems. To correct these problems, the model here was estimated using Driscoll and Kraay (1998) standard errors as implemented by Hoechle (2007). This estimation accounts for heteroskedasticity and Cross-Sectional Dependence problems. Moreover, this option allowed us to correct the auto-correlation of any order. Our reliance on the fixed-effect estimator was based on the Hausman (1978) specification test. We estimated two regressions for the specification model.

The following is a simple linear specification, which forms the basis for subsequent estimation:

\[
\ln V_{it} = a + \gamma \ln EDU_{it} + \delta \ln PEC_{it} + \eta \ln PRI_{it} + \nu \ln IND_{it} + \xi \ln UBN_{it} + \\
\psi \ln GINI_{it} + \sigma \ln UNE_{it} + \lambda \ln SAL_{it} + \varphi \ln EPI_{it} + \mu_{it}
\]

(1)

Note that \( V_{it} \) is the homicide rate during the period \( t \) for the city \( i \); \( EDU_{it} \) is the secondary education coverage of the population by city; \( PEC_{it} \) is the primary education coverage by city; \( PRI_{it} \) is the prices level by city; \( IND_{it} \) is the indigence
level by city; $UBN_{it}$ is the unsatisfied basic needs level by city; $GINI_{it}$ is the coefficient of the GINI index by city; $UNE_{it}$ is the unemployment rate by city; $SAL_{it}$ is the real salaries level by city; and $EPI_{it}$ is employments per industry, in the period $t$ for the city $i$.

To study violence and its interactions with socio-economic conditions, this analysis employed a panel data model with city-specific fixed-effect in order to capture all of the features specific to each city (i.e., the level of development or socio-economic indicators). The fixed-effect model is defined through the F-test for ordinary least squares (OLS) and fixed-effects and the Hausman test for fixed effects and random effects (RE) models. Formally, the model is the following:

$$y_{it} = \alpha + x_{it} \beta + v_i + \epsilon_{it}, \epsilon_{it} \sim IID \ (0, \sigma^2)$$  \hspace{1cm} (2)

The subscript $i$ represents each city in the year $t$; $y$ is the dependent variable of violence; $\chi$ is the vector containing the variables measuring objective conditions; $v_i$ is the unobserved individual effect; $\epsilon_{it}$ is the error term; and $\alpha$ could represent motivation, ability, genetics (micro-data) or historical and institutional factors (city-level data).

The model (1) is estimated with a fixed-effects estimator, which is the natural estimator that should be used, as the cities in the sample are fixed. The fixed effects estimator subtracts the over-time average of the equation for each city from the estimated equation. Because of this so-called within-transformation subtraction, the individual city effects $u_i$ are eliminated, and the coefficients are estimated based upon the time variation within each cross-sectional unit only. Any correlation between the fixed effects and the explanatory variables is therefore rendered unproblematic.

$$y_{it} - \bar{y}_i = (x_{it} - \bar{x}_i)\beta + (u_{it} - \bar{u}_i)$$ \hspace{1cm} (3)

where

$$\bar{x}_i = \frac{1}{T} \sum_{t=1}^{T} x_{it} \text{ and } \bar{u}_i = \frac{1}{T} \sum_{t=1}^{T} u_{it}$$

$$\hat{\beta}_{FE} = (\sum_{i,t}^{I} \hat{x}_{it}'\hat{x}_{it})^{-1} \sum_{i,t}^{I} \hat{x}_{it}'\hat{y}_{it}$$

where

$$\hat{x}_{it} = (x_{it} - \bar{x}_i) \text{ and } \hat{y}_{it} = y_{it} - \bar{y}_i$$
The following tests were carried out to determine the robustness of the estimations (De Hoyos and Sarafidis, 2006):

**i. Frees’ test**

Frees (1995, 2004) asserted that his statistic should be based upon the sum of the squared rank-correlation coefficients, which equals the following:

\[
R_{AVE}^2 = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{r}_{ij}
\]

(4)

As shown by Frees, a function of this statistic follows a joint distribution of two independently drawn \(x^2\) variables. In particular, Frees demonstrates that

\[
FRE = N(R_{AVE}^2 - (T - 1)^{-1}) \xrightarrow{d} Q = a(T) \left(x_{1,T-1}^2 - (T - 1)\right) + b(T) \left(x_{2,T(T-3)/2}^2 - T(T - 3)/2\right)
\]

(5)

**ii. Wald test**

A test for heteroskedasticity is used to estimate the error process that may be homoskedastic within cross-sectional units. This test estimates a modified Wald statistic for group-wise heteroskedasticity in the residuals of a fixed effects regression model. The null hypothesis specifies that \(\sigma_{it}^2 = \sigma^2\) for \(i = 1, ..., N_g\), where \(N_g\) is the number of cross-sectional units. Furthermore, \(\hat{\sigma}_{it}^2 = T_i^{-1} \sum_{\ell=1}^{T_i} e_{it}^2\) will be the estimator of the ith cross-sectional unit’s error variance, based upon the \(T_i\) residuals \(e_{it}\) available for that unit. We next defined (Greene, 2011; Baum, 2001).

\[
V_i = T_i^{-1}(T_i - 1)^{-1} \sum_{\ell=1}^{T_i} (e_{it}^2 - \hat{\sigma}_{it}^2)^2
\]

(6)

as the estimated variance of \(\hat{\sigma}_{it}^2\). The modified Wald test statistic, defined as

\[
W = \sum_{i=1}^{N_g} \frac{(\hat{\sigma}_{it}^2 - \sigma^2)^2}{V_i}
\]

(7)

was distributed as \(\chi^2[N_g]\) under the null hypothesis. The null hypothesis is homoskedasticity (or constant variance). Above, we rejected the null hypothesis and conclude heteroskedasticity.
iii. Pesaran's CD test

In the context of seemingly unrelated regressions estimation, Breusch and Pagan (1980) suggested the use of a Lagrange Multiplier (LM) statistic. Pesaran (2004) presented the following alternative:

\[
CD = \sqrt{\frac{2T}{N(N-1)}} \left( \sum_{t=1}^{N-1} \sum_{j=t+1}^{N} \hat{\rho}_{ij} \right)
\]  

(8)

and showed that under the null hypothesis, there was no cross-sectional dependence \( CD \overset{d}{\rightarrow} N(0; 1) \) for \( N \rightarrow \infty \) where \( T \) is sufficiently large. In the case of unbalanced panels, Pesaran (2004) suggested a slightly modified version of equation 8, which is the following:

\[
CD = \sqrt{\frac{2}{N(N-1)}} \left( \sum_{t=1}^{N-1} \sum_{j=t+1}^{N} \sqrt{T_{ij}} \hat{\rho}_{ij} \right)
\]  

(9)

iv. Friedman's test

Friedman (1937) suggested a non-parametric test established on Spearman's rank correlation coefficient. Friedman's statistic is based on the average Spearman correlation and is given by

\[
R_{AVE} = \frac{2}{N(N-1)} \sum_{t=1}^{N-1} \sum_{j=t+1}^{N} \hat{r}_{ij}
\]  

(10)

where \( \hat{r}_{ij} \) is the sample estimate of the rank correlation coefficient of the residuals. Through this model (10), large values of \( R_{AVE} \) show the presence of non-zero cross-sectional correlations.

v. Wooldridge test

The Wooldridge test for serial autocorrelation determines the presence of serial autocorrelation as an indication that the dependent variable is characterised by persistent or mean-reverting dynamics, implying that the omitted variables have a large impact on the dependent variable. This technique captures the cumulative effect of multiple unobserved variables from year to year in individual departments and enables the effects of the remaining independent variables to be estimated more directly. Wooldridge’s method uses the residuals from a regression on first-differences. First-differencing the data in the model eliminates
the individual-level effect, the term based on the time-invariant covariates and the constant.

\[
\Delta y_{it} = (X_{it} - X_{it-1}) \beta_1 + \epsilon_{it-1}
\]

(11)

\[
\Delta y_{it} = \Delta X_{it} \beta_1 + \Delta \epsilon_{it}
\]

(12)

where \(\Delta\) is the first-difference operator.

Wooldridge’s method begins by estimating the parameters \(\beta_1\), by regressing \(\Delta y_{it}\) on \(\Delta X_{it}\) and obtaining the residuals \(\hat{\epsilon}_{it}\). Central to this procedure is Wooldridge’s observation that if the \(\epsilon_{it}\) is not serially correlated, then \(\text{Corr}(\Delta \epsilon_{it}, \Delta \epsilon_{it-1}) = -0.5\). Given this observation, the procedure regresses the residuals \(\hat{\epsilon}_{it}\) from the regression with first-differenced variables on their lags and tests that the coefficient on the lagged residuals is equal to \(-0.5\) (Wooldridge, 2010, Drukker, 2003). The null hypothesis is no serial correlation. Above, we failed to reject the null hypothesis and concluded that the data did not have first-order autocorrelation.

vi. Fixed effects regression with Driscoll and Kraay standard errors

To test for the heteroskedasticity problem or Cross-Sectional Dependence in the estimations with fixed effects, we used fixed effects regression with Driscoll and Kraay (1998) standard errors. The respective fixed-effects estimator was implemented in two steps. In the first step, all model variables \(z_{it} \in \{y_{it}, x_{it}\}\) were within-transformed as follows (Hoechle, 2007):

\[
\bar{z}_{it} = z_{it} - \bar{z}_i + \bar{z} \quad \text{where} \quad \bar{z}_i = T_i^{-1} \sum_{t} z_{it} \quad \text{and}
\]

\[
\bar{z} = (\Sigma T_i)^{-1} \sum_i \sum_t z_{it}
\]

(13)

The second step then estimated the transformed model:

\[
\tilde{y}_{it} = x'_{it} \theta + \tilde{\epsilon}_{it}
\]

(14)

The advantage of the FE is that the presence of city-specific effects can be tested, and it is possible to control for unit-specific omitted variables. Regarding the heteroskedasticity problem or Cross-Sectional Dependence in the estimations with fixed effects, we used a fixed effects regression with Driscoll and Kraay (1998) standard errors. This model is a covariance matrix estimator, which produces standard errors that are robustly resistant to the violations of the Gauss-
Markov assumptions. Thus, we are relying on a fixed-effect model with corrections for heteroskedasticity and auto-correlation (Hoechle, 2007).

4. Empirical Findings and Econometric Results

Table 2 depicts the regression results of pooled OLS and panel data regression models. Pooled OLS is considered the base model under the assumption of homoskedasticity and is marked by the absence of serial correlation and contemporaneous correlation. In the presence of these problems, coefficient estimates may not be optimal. Along with pooled OLS, we also applied pooled OLS with panel corrected standard errors (PCSE) to develop rid-off panel level heteroskedasticity, serial auto-correlation and contemporaneous correlation problems proposed by Beck and Katz (1995).

Nevertheless, in this case, there was no problem of contemporaneous correlation, as no single year was common to all units of analysis. Therefore, we considered only heteroskedasticity and the serial autocorrelation problem. Because the PCSE estimator of Beck & Katz (1995) has poor finite sample features when a panel’s cross-sectional dimension is too large as compared to its time dimension, we performed the model using the method suggested by Driscoll and Kraay (1998). However, because pooled OLS estimates fail to consider the unobservable city-specific and time-specific effects, the model was once again applied assuming that city-specific effects are fixed and random.

The Hausman specification test suggests that using a fixed effects model is appropriate. Therefore, we relied on a fixed-effect model with correction for heteroskedasticity and auto-correlation corrected standard errors as proposed by Driscoll and Kraay (1998). Moreover, we have already described the Parks-Kmenta method assessments of FGLS. We observed that OLS estimators and a random effect estimator overestimate the fixed-effect models and underestimate the standard errors. We also observed that the GINI index has a positive impact on homicide rates but is insignificant in the case of the fixed effects model and the Driscoll and Kraay model with fixed effects.

The specifications of equation (1) were estimated in terms of the Colombian levels of violence. In Table 2, the different relationships between homicide rates, levels of economic development of cities, poverty, income distribution, human capital, and labour market are shown. The results present several findings that confirm previous studies and the forecasts of the theoretical model of crime developed in recent years, which suggest that socio-economic development is an important strategy to strengthen security and decrease crime and violence in cities.
Table 2 Estimation Techniques. Dependent variable: Violence measured by homicide rate.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Ordinary Least Squares (OLS)</th>
<th>Fixed Effects</th>
<th>Random Effect</th>
<th>Feasible Generalised Least Squares (FGLS)</th>
<th>OLS with Panel Corrected Standard Errors (PCSE)</th>
<th>Newey-West</th>
<th>Robust standard errors with heteroskedasticity autocorrelation cross-sectional dependence (Driscoll-Kraay)</th>
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<td>Constant</td>
<td>5.223 ^a</td>
<td>5.223 ^a</td>
<td>5.223 ^a</td>
<td>5.223 ^a</td>
<td>5.223 ^a</td>
<td>5.223 ^a</td>
<td>11.89 ^a</td>
</tr>
<tr>
<td>(1.349)</td>
<td>(1.302)</td>
<td>(1.290)</td>
<td>(1.281)</td>
<td>(1.349)</td>
<td>(1.355)</td>
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<td>Secondary education coverage</td>
<td>-1.502 ^a</td>
<td>-1.502 ^a</td>
<td>-1.502 ^a</td>
<td>-1.502 ^a</td>
<td>-1.502 ^a</td>
<td>-1.502 ^a</td>
<td>-4.661 ^a</td>
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<tr>
<td>(0.425)</td>
<td>(0.448)</td>
<td>(0.444)</td>
<td>(0.562)</td>
<td>(0.425)</td>
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<td>-0.072 ^b</td>
<td>-0.072 ^b</td>
<td>-0.072 ^b</td>
<td>-0.072 ^b</td>
<td>-0.072 ^b</td>
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<tr>
<td>(0.040)</td>
<td>(0.058)</td>
<td>(0.057)</td>
<td>(0.040)</td>
<td>(0.046)</td>
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<td>0.352 ^a</td>
<td>0.352 ^a</td>
<td>0.352 ^a</td>
<td>0.352 ^a</td>
<td>0.352 ^a</td>
<td>0.594 ^a</td>
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<td>(0.037)</td>
<td>(0.041)</td>
<td>(0.066)</td>
<td>(0.108)</td>
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<td>0.290</td>
<td>0.290</td>
<td>0.290</td>
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<tr>
<td>(0.216)</td>
<td>(0.201)</td>
<td>(0.199)</td>
<td>(0.216)</td>
<td>(0.426)</td>
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<td>Indigent</td>
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<td>0.111</td>
<td>0.111</td>
<td>0.111</td>
<td>0.111</td>
<td>0.111</td>
<td>0.116</td>
</tr>
<tr>
<td>(0.141)</td>
<td>(0.132)</td>
<td>(0.131)</td>
<td>(0.141)</td>
<td>(0.122)</td>
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<tr>
<td>Unsatisfied basic needs</td>
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<td>0.687</td>
<td>0.687</td>
<td>0.687</td>
<td>0.687</td>
<td>1.447</td>
<td>1.47</td>
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<td>(1.490)</td>
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<tr>
<td>GINI</td>
<td>0.482 ^c</td>
<td>0.482 ^c</td>
<td>0.482 ^c</td>
<td>0.482 ^c</td>
<td>0.482 ^c</td>
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<td>(0.276)</td>
<td>(0.264)</td>
<td>(0.333)</td>
<td>(0.276)</td>
<td>(0.675)</td>
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<td>Unemployment</td>
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<td>0.084</td>
<td>0.084</td>
<td>0.222</td>
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<tr>
<td>(0.098)</td>
<td>(0.087)</td>
<td>(0.159)</td>
<td>(0.098)</td>
<td>(0.301)</td>
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<td>Real salaries</td>
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<td>-0.371</td>
<td>-0.371</td>
<td>-0.371</td>
<td>-0.371</td>
<td>-0.255</td>
<td>-2.55</td>
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<tr>
<td>(0.267)</td>
<td>(0.276)</td>
<td>(0.341)</td>
<td>(0.267)</td>
<td>(0.250)</td>
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<tr>
<td>Employments level per industry</td>
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<td>-1.632 ^a</td>
<td>-1.632 ^a</td>
<td>-1.632 ^a</td>
<td>-1.632 ^a</td>
<td>-1.632 ^a</td>
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<td>(0.502)</td>
<td>(0.452)</td>
<td>(0.659)</td>
<td>(0.502)</td>
<td>(0.676)</td>
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<tr>
<td>F statistics</td>
<td>20.97</td>
<td>24.34</td>
<td>27.08</td>
<td>24.34</td>
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<tr>
<td>R-squared</td>
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<td>0.286</td>
<td>0.255</td>
<td>0.255</td>
<td>0.255</td>
<td>0.286</td>
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Statistical Tests for Fixed Effects

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<th>Test</th>
<th>OLS vs. FE</th>
<th>Time fixed effects test: Prob&gt;F</th>
<th>Entities fixed effects test: Prob&gt;F</th>
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<td>F-test for</td>
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<td>0.011</td>
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<tr>
<td>Hausman test chi²</td>
<td>26.03</td>
<td>Pesaran test 32.121</td>
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<tr>
<td>Prob&gt;chi²</td>
<td>0.000</td>
<td>Pr 0.000</td>
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<tr>
<td>Frees test</td>
<td>3.829</td>
<td>Friedman test 480.61</td>
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</tr>
<tr>
<td>Pr</td>
<td>0.000</td>
<td>Pr 0.000</td>
<td></td>
</tr>
<tr>
<td>Wald test chi²</td>
<td>0.720</td>
<td>Wooldridge test F 556.84</td>
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</tr>
<tr>
<td>Prob&gt;chi²</td>
<td>0.998</td>
<td>Pr 0.000</td>
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Notes: Figures in the parentheses are standard errors. ^aSignificant at the 1% level, ^bSignificant at the 5% level, ^cSignificant at the 10% level.
Human capital, as measured by the level of primary and secondary education coverage, had a negative and significant impact on current homicide rates. The higher the level of human capital in a city, the lower the homicide rate will be. This finding suggests that human capital leads to a reduction in violence over time and that education plays an important role in effective strategies to reduce and control violence. This result is consistent with the work of Velez et al. (2002) and Ayres (1998). In the Colombian context, Velez et al. (2002) demonstrated that another effect of violence is the reduction of human capital stock due to decreases in investments in human capital. In the Latin American context, Ayres showed that crime and violence erode the development of human capital because increases in security expenditures (e.g., police forces or expanding prisons) reduce investments in human capital. Buonanno and Leonida (2006 and 2009) demonstrated that education has a negative and significant effect on crime rate, and higher education rates reduce crime due to higher labour market opportunities (employment and wages).

Moreover, these estimations demonstrate the important impact of human capital on violence. The term human capital refers to the increases in productivity or efficiency that society acquires with improved levels of education or training. The benefits generated by increasing levels of education or technological innovations that are liberally diffused are considered a social effect. Human capital does not refer to changes in individuals. Economies with higher levels, or higher averages, of human capital are more productive than those with lower levels. In other words, the level of such capital is reflected in social productivity rates and in economic and social stability.

The variable of prices has a positive and significant influence on homicide rates, indicating that an increase in prices generates a higher rate of violence. Lagrange (2003) showed that an increase in opportunities to commit crimes exists when a consumer price trend is increased, which is consistent with our results. In the Colombian case, Dube and Vargas (2008) demonstrated that price shocks affect crime and violence in different ways depending on the factor intensity of the commodity; i.e., the price of natural resources, which are capital intensive, is positively related to violence and crime. When the prices increase, the increase in crime and violence is less pronounce in municipalities that produce more of these natural resources.

The coefficients of the estimations support the hypothesis that poverty indicators (poverty level, indigent and unsatisfied basic needs) and unequal distribution of income have positive effects on violence in Colombian cities. The effect of poverty on the homicide rate shows that a percentage point increase in the rate of poverty increases the homicide rate by 0.20 per 100,000 people. Some of the most recent research, for example, Holmes et al. (2010), has asserted that poverty, social inequality, socio-economic variables and narcotrafficking are the
causes of violence in Colombia. Economic inequality, measured as the GINI index, suggests that higher inequality increases the incidence of homicide; a 1% increase in inequality increases the rate of homicides by 0.11 per 100,000 inhabitants. Moreover, the combinations of significant effects due to the economic cycle and income distribution indicate that decreases in the poverty rate and the rate of indigence may be associated with large decreases in the homicide rate (Da Mata et al., 2007). Likewise, income inequality and poverty levels are strong predictors of the violence level of a region, i.e., violence is higher in regions where higher proportions of people are economically deprived (OMCT, 2005). Moreover, our results are consistent with those of Bourguignon et al. (2002), who concluded, in the Colombian context, that criminal activities are most often carried out by people whose income is below 80% of the mean level.

The results of the market labour variables indicate that unemployment is directly related to violence, whereas higher salaries and higher rates of employment generate lower homicide rates; an increase of 1% in real wages decreases the rate of homicides by 0.25 per 100,000 populations. Several studies have demonstrated that poor labour market prospects should lead to an expectation of significantly higher levels of violence and crime (Entorf, 2009, Lee and Holoviak, 2006, Andres, 2002, Cerro and Meloni, 2000).

This paper has several political implications. The strategies and political instruments aimed at reducing violence must address a variety of different issues related to socio-economic development, including human capital, poverty, inequality and labour markets, rather than simply pouring money into security enforcement and other forms of criminal deterrence. Such strategies would be more effective and would strengthen welfare, economic growth and development.

5. Conclusions

This study uses several empirical approaches to analyse the effects of socio-economic development on violence using seven metropolitan areas in Colombia as a case study. The study examines long- and short-term implications of several categories of development, including human capital, poverty, inequality and market labour, on violence, considering their interrelationships in this context. The contribution of this study is twofold. First, this study extends the empirical literature on violence and economic development in the context of a developing economy such as Colombia, and second, it provides empirical evidence in favour of the assertion that socio-economic determinants of violence, such as human capital, poverty, inequality and variables of market labour, are important in determining the policies to reduce violence in Colombian cities.
The main findings of this analysis indicate that economic dynamics have direct effects on urban homicides. Crisis periods of economic activity generate an escalation in the homicide rate; whereas in growth periods, the homicide rate tends to decrease. Likewise, evidence indicates that economic shocks, such as those occurring in several Colombian cities due to drug trafficking, should help to explain the tendencies of homicide rates to increase during certain periods and decrease in other periods in which different measures have been adopted.

To determine the various relationships between violence and its causes and various categories of development, we employed different econometric approximations. The results suggest that homicide rates are directly related to prices, poverty, inequality and unemployment; whereas education, salaries and employment per industry have an inverse impact on these rates. Therefore, human capital, poverty, inequality and labour market factors impact urban violence levels. Policy makers should consider a combination of economic dynamics and redistributive politics as a strategy to decrease inequality and poverty and increase human capital in order to improve security and decrease crime and

Appendix 1
Summary of the main variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Main sources</th>
</tr>
</thead>
</table>
| Violence - homicide rates per 100,000 population by city | -National Institute of Legal Medicine, the National Policy of Colombia.  
-Centre of Criminalist Research (DIJIN)  
-Information systems SIEDCO  
-CERAC (Conflict Analysis Resource Center) |
| Education: (Secondary education coverage and Primary education coverage). The coverage rate is the net percentage of students enrolled at an educational level that are age appropriate for that level, and the total population in the age range appropriate to study at that educational level | The Colombian education ministry |
| Prices measured as consumer price index | DANE in the chapter consumer price index |
| Poverty and indigent according to methodology DANE | DANE in the chapter poverty and inequality |
| Unsatisfied basic needs according to methodology used by CEPAL and DANE | DANE in the chapter unsatisfied basic needs |
| GINI coefficient measures the inequality | DANE in the chapter poverty and inequality |
| Unemployment rate and real salaries according to methodology used by DANE | DANE in the chapter labour market |
| Employments level per industry | DANE in the chapter annual survey of industries |
References


