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Income Inequality and Violent Crime: Evidence from Mexico's Drug War

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Abstract: Evidence of a causal effect of inequality on crime is scarce in developing countries. This paper estimates the effect in a unique context: Mexico's Drug War. The analysis exploits a unique dataset containing inequality and crime statistics for more than 2,000 Mexican municipalities over a 20-year period. An instrumental variable for the Gini coefficient combines the initial income distribution at the municipality level with national trends. The results indicate that a one-point increment in the Gini between 2006-2010 translates into an increase of over 10 drug-related homicides per 100,000 inhabitants. These effects are smaller between 1990 and 2005. The fact that the effect found during the Drug War is substantially higher is likely because the cost of crime decreased with the proliferation of gangs (lowering the marginal cost of criminal behavior), which, combined with rising inequality in some municipalities, increased the expected net benefit of criminal acts after 2005.

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1. Introduction

The question of what is the effect of inequality on crime has been a matter of interest among many researchers and policy analysts. While most of the literature on this topic finds a positive effect of inequality on crime, the empirical evidence has fallen short in establishing an unambiguous direction of causality (see Pridermore, 2011), as well as on whether the effect holds for different types of violent crime. Moreover, when focusing on developing countries the available evidence is weaker given that reliable and comparable crime statistics tend to be scarce. In addition, scholars have faced other major challenges when delving into this subject. For example, cross-country studies are usually biased by measurement error and omitted variables problems, and they are also limited by small-sample sizes. Reverse causality is a matter of concern, since increasing crime rates might also affect inequality by, for example, encouraging richer residents to move out of violent locations.

Neumayer (2005) points out that focusing on within-country variation could be a remedy to the difficulty to control for confounding factors at the country level and to the small-sample problem that arises in cross-country analysis. Nonetheless, even when those problems have been addressed, the reverse causality problem remains. In this paper, we take a step forward seeking to tackle the aforementioned challenges by focusing on within-country variation at the municipal level in crime and inequality in Mexico; and using the predicted income distribution of a municipality, based on the initial income distribution of that area and the national patterns of income growth, we construct an instrument (predicted Gini) for the observed Gini coefficient (Boustan et al., 2012). This instrument, by construction, isolates the component of change in inequality that is driven by national trends, and it is not influenced by local factors such as the homicide rate.

We focus our attention on Mexico as it represents a unique case among developing nations. First, in terms of crime rates, while the total rate of homicides in Mexico followed a downward pattern for the 1990-2005 period, the picture is totally different for the period from 2005 to 2010. For example, in 2005 the total rate of homicides was close to 11 deaths per 100,000 individuals, while by 2010 it was 18.5 deaths (Mexico's National Public Security System, SNSP, 2011). This sharp increase in the rate of total homicides is mainly due to the rising number of violent crimes associated with drug-related activities e.g., according to the SNSP, in 2005 there were more than 7,000 deaths related to non-drug crimes, nearly double the number of deaths caused by drug-related homicides; by 2010 the situation had completely turned around, that is, the number of drug-related homicides more than tripled the number of non-drug related homicides (see also Rios, 2012). To illustrate the economic implications of this matter, victimization surveys estimate that in 2010 crime cost victims losses valued at US$12.9 billion. In addition, for that same year, 42.8 percent of Mexico's firms paid for private security, spending about 2.2 percent of their annual sales on these services (IFC and WB, 2012); and reductions in economic activity and growth were found at the municipal level between 2006 and 2010 (Robles et al., 2013, and Enamorado et al., 2013).

Second, while there have been major advancements in reducing income inequality in Mexico over the last fifteen years—with a decline from 0.547 to 0.475 of the Gini coefficient for the distribution of household per capita income (Lustig et al., 2012)—heterogeneity across regions remains. Between

1990 and 2005, about 90 percent of the municipalities in Mexico registered a decline in income inequality, while between 2005 and 2010 about 78 percent of the municipalities experienced a reduction of their Gini coefficient. Despite an overall decrease in the Gini coefficient at the national level, many municipalities experienced an increase in inequality during these periods and Mexico is still one of the countries in Latin America where low-income mobility is a widespread problem (see Cuesta et al., 2011; Bourguignon 2004).

Our results from linear regression models that do not account for reverse causality and omitted variables predict that, in the case of Mexico, an increase in inequality is linked to a decrease in homicides. We argue that this result might be driven by selective outmigration of richer residents to safer municipalities and by other channels through which crime might affect the distribution of income. Nonetheless, when we use our proposed instrument to tackle the endogeneity problem, we find that for the period that goes from 2005 to 2010, an increase of one unit in the Gini coefficient (our income inequality measure) translates in more than 6 additional deaths per 100,000 individuals when focusing on the total homicide rate. Moreover, this effect is larger if we focus just on drug-related crimes, where an increase in the Gini coefficient of one unit is associated with an increase of more than 10 deaths. On the other hand, in the case of non-drug related homicides, we do not find any evidence suggesting that changes in inequality play a role in determining those types of crimes during Mexico's Drug War. We do find that inequality increased those type of crimes since 1990, but the effects are substantially smaller in magnitude. This finding shows the importance of the lower costs of criminal activity brought about by the expansion of drug trafficking gangs after 2005, in shaping the effects of income inequality on criminal activity. The results presented are unaffected by alternative specifications and different robustness checks.

The rest of this paper proceeds as follows. Section 2 presents a literature review of the theoretical and empirical evidence on this subject; Section 3 presents long and medium-run trends of subnational income inequality and facts on Mexico's Drug War and the associated spike in violent crime rates. Section 4 describes methodology and data; Section 5 lays out the empirical strategy, with a special focus on how we recover income inequality measures at the municipal level in Mexico and how our proposed instrument was constructed. Section 6 presents our main findings, and Section 7 concludes.

2. Previous Literature on the Links between Income Inequality and Crime

Within the literature on the effects of inequality and poverty on crime there are two distinctive and complementary approaches. First, we have the sociological theories of crime, which center their attention on the emotional feelings that cause people to become delinquents. In these theories, poverty and inequality cause social tension, anxiety, and strain, which lead people to become more violent (recent empirical work presenting evidence supporting those theories can be found in Fajnzylber, Lederman, and Loayza [1998, 2002a, 2002b], and Whitworth, 2012). The second approach includes the concept of criminal behavior as a cost-benefit calculation, introduced to the economics literature by Becker's (1968) seminal work. In a nutshell, Becker proposes that crime is a function of an individual's calculations in weighing the expected utility of crime against the utility of using the same time and resources to pursue legal activities. Thus, it is not difficult to see that in this theory poor individuals living in an unequal setting will be more prone to recur to illegal activities, as their outside options (i.e., legal activities) do not offer higher benefits in the short term (Freeman, 1999). These calculations behind are influenced by the deterrence mechanisms and penalties put in place to prevent crime. Conversely to the case described above, the poor may find non-criminal activities preferable if the net benefit of crime (after discounting penalties) is lower than their poverty status.

Regardless of the mechanism(s) behind (rational calculation vs. emotional motivations originated by social exclusion), both set of theories strongly suggest that inequality and poverty foster crime. Many authors have tried to test these theories empirically obtaining mixed results. For example, Ehrlich (1973) finds that in the United States (1940-1970), inequality and income are positively correlated with both property (robbery, burglary, larceny, and auto theft) and violent crimes (murder and rape). Blau and Blau (1982), argue that economic inequalities are the root of violent crime in the United States. In their findings, when explaining crime, the role of variables such as poverty is outweighed by the predicting power of inequality. In this same line of work, Kelly (2000) finds that in urban areas in the United States poverty and police activity are significantly correlated with property crimes, while inequality has no effect on such types of crimes. On the other hand, when focusing on violent crimes, inequality is the main driver.

Contrasting Kelly's (2000) results, Fajnzylber, Lederman, and Loayza (2002b) find, in their analysis of data on homicides and robberies in a cross-section of both industrialized and developing countries, that inequality and poverty increase *both* robberies (here, a proxy for property-related crimes) and homicides (a proxy for violence). Neumayer (2005) directly calls into question Fajnzylber, Lederman, and Loayza's (2002b) results; arguing that by increasing the sample size of countries, inequality—measured as the Gini coefficient—is no longer statistically significant when predicting violent crime.[5] Moreover, Pridemore (2011) criticizes the large cross-country literature that studies the link between inequality and homicide rates as most of those fail to control for poverty rates, which is the most consistent predictor of area homicide rates in the US empirical literature. Pridemore replicated previous cross-country studies that found a statistical significant relation between inequality and homicides, finding that when the models controlled for poverty rates, such relationship was not significant anymore.

Brush (2006) finds mixed results in terms of the effect of income inequality on crime rates using county level data for the United States. Using cross-sectional analysis he does find that income inequality promotes crime, although when centering his attention on a time series analysis he finds that income inequality reduces crime. Poveda (2011) finds that poverty and inequality both have positive impacts on the rate of homicide in seven major Colombian cities. Similarly, using a sample

[5] Neumayer (2005) used 59 countries in his sample. Fajnzylber, Lederman, and Loayza's (2002b) have 45 countries in their sample.

of OECD, Central and South American countries, Nadanovsky and Cunha-Cruz (2009), find that low inequality leads to a reduction in homicide rates. Demombynes and Ozler (2005) find that higher inequality in South Africa is associated with higher rates of property and violent crimes at the neighborhood level. Finally, in a recent study using inequality data for the United States at the state level, Chintrakarn and Herzer (2012) find that inequality has a negative effect on crime. Their explanation for this counterintuitive result is that the higher the inequality within a state, the larger the demand for security services, which leads to a reduction in crime.

As this succinct literature review shows, empirical evidence on the effects of inequality over crime is mixed. In order to further analyze this question, this paper focuses on within-country variation in income inequality and crime rates using a unique data set of Mexican municipalities from 1990 to 2010. Additionally, the paper uses differentiated homicide rates, thus distinguishing whether the impact of inequality over crime rates is more pronounced for common crime, organized crime, or both. In particular, we expect that the effect of inequality on organized crime would be exacerbated in the context of Mexico's Drug War. The literature has shown that the proliferation of gangs tends to increase the propensity to commit crimes as they facilitate access to knowledge and logistics associated with criminal activities (Thornberry et al. 1993; Zhang et al. 1999; Gatti et al. 2005). In other words, gangs tend to lower the marginal cost of criminal behavior. Proliferation of gangs would thus have a greater impact on crime levels in cities with a high degree of poverty and inequality, since higher costs are more likely to be a binding constraint for crime activity among individuals with less economic resources. The splintering of drug-trafficking gangs and their geographic diffusion during Mexico's Drug War might have facilitated criminal behavior disproportionally among cities that became poorer and more unequal during this period. At the same time, increasing levels of inequality associated with rich individuals becoming richer would tend to exacerbate these effects, by increasing the expected pay-off of criminal activity. In other words, if the cost of crime decreases and the income differences between the poor and the rich become larger, the expected net benefit from criminal acts such as extortion, kidnapping and theft would increase.

3. Income Inequality and Crime in Mexico: Some Stylized Facts

Trends in Income Inequality in Mexico

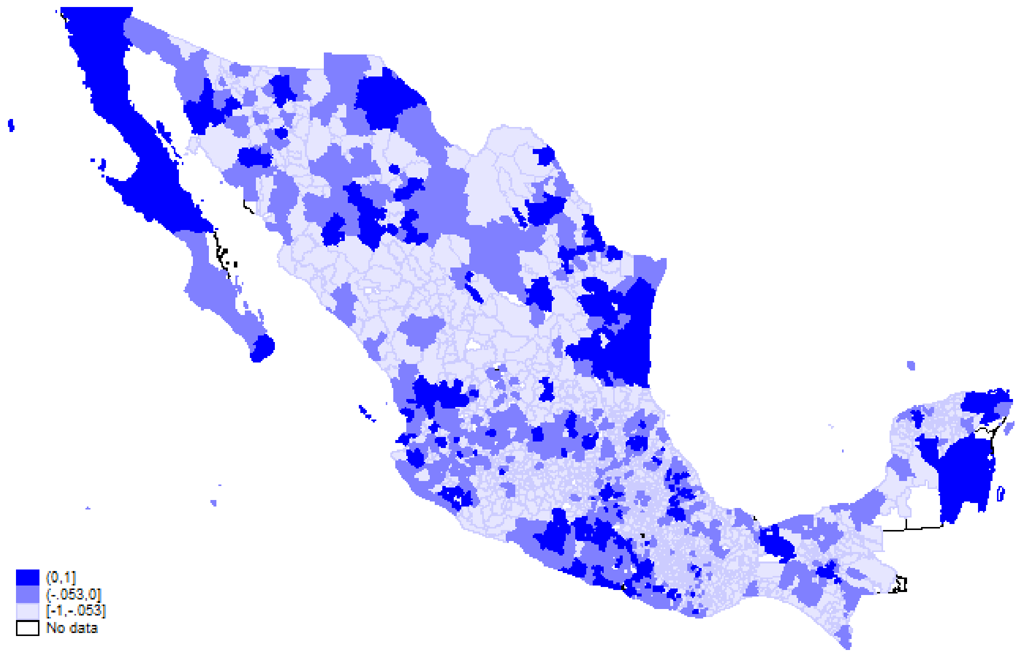
Although income inequality measured by the Gini coefficient declined by about six points from 1996 to 2010 (Lustig et al. 2012), recent figures show that this trend has slowed down for the period 2005-10, and displays a slight reversal between 2010 and 2012 (INEGI, 2013). For the same periods, there is significant within-country variability. Over the long-run (1990-2010), about 90 percent of the municipalities in Mexico observed a reduction in Gini coefficient, while over the medium-run (2005-2010) about 73 percent of the municipalities had a decline of inequality.

Figures 1a and 1b show the long and medium-run changes in the Gini coefficient at the municipality level with respect to the national average (weighted average of -5.3 Gini points for the period 1990-

2010, and -3.7 for the period 2005-2010). Between 1990 and 2010, about 67 percent of the more than 2,000 municipalities in Mexico had a speed of reduction of the Gini coefficient above the national average (representing about 49 percent of total population); while 23 percent observed a decline in inequality over the same period but lower than the national average; and the remaining 10 percent experienced an increase in inequality (33 percent and 18 percent of total population, respectively). For the medium-run period of 2005-2010, about 50 percent of municipalities had a decline in inequality above the national average, and 28 percent had a decline below the national average (53 percent and 28 percent of the total population, respectively); while 22 percent of municipalities observed an increase in the Gini coefficient over this period (19 percent of total population). These numbers confirm that, although income inequality declined in the majority of municipalities in Mexico both over the long and medium-run, there is a non-trivial number of municipalities in which income inequality increased, particularly between 2005-2010, overlapping with Mexico's Drug War.

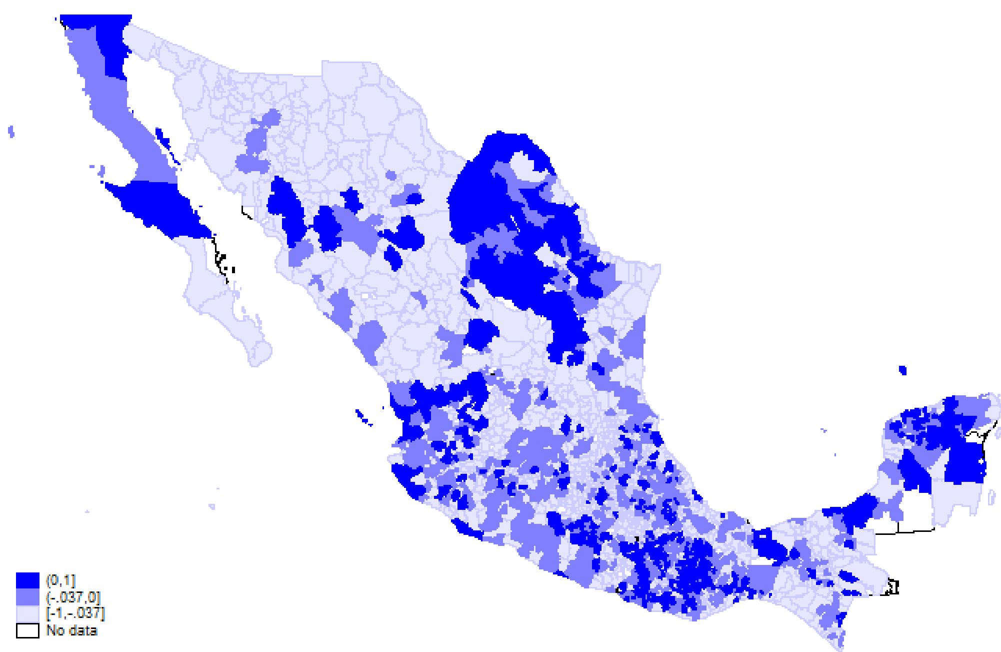
Figure 1: Long and medium-run variation in income inequality at municipal level vs. national average *(1990-2010 and 2005-2010)*

1.a: Change in local Gini coefficient, 1990-2010



Source: Author's own estimations using ENIGH and Population Census/Counts.
Note: This map reports The change in Gini between 1990-2010 by municipality. The change of -0.053 was the national change

1.b: Change in local Gini coefficient, 2005-2010



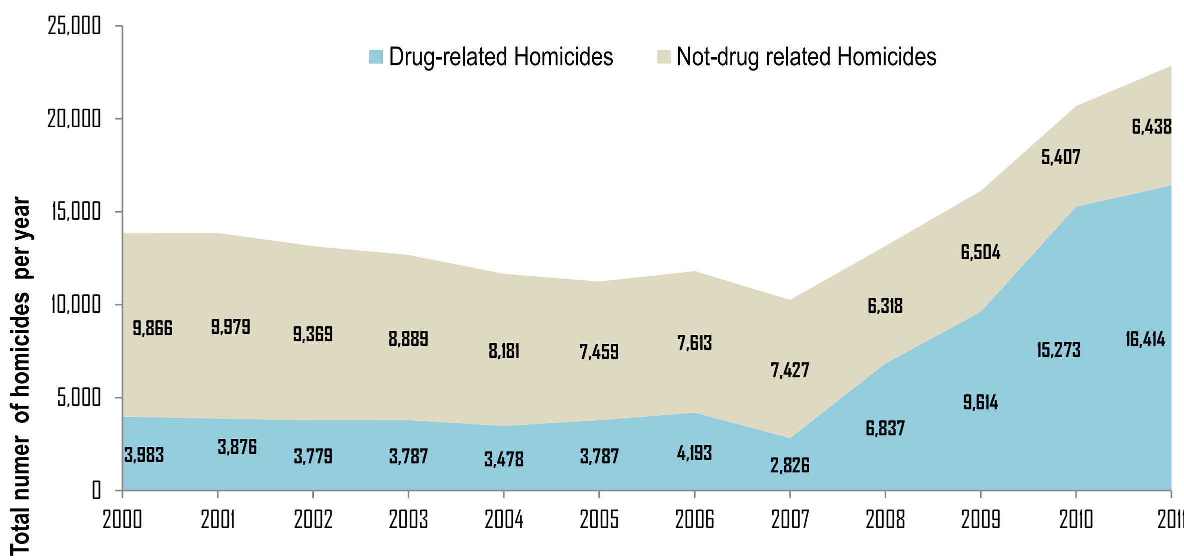
Source: Author's own estimations using ENIGH and Population Census/Counts.
Note: This map reports The change in Gini between 2005-2010 by municipality. The change of -0.037 was the national change

Trends in Crime and Violence in Mexico

The annual number of homicides in Mexico almost doubled between 2000 and 2011, from 13,849 to 22,852, according to official statistics reported by Mexico's Technical Secretariat of the National Public Security Council (SNSP), a federal entity dependent of the Ministry of Interior (Figure 2). These numbers correspond to a homicide rate of 13.73 per 100,000 population in 2000 and 19.75 per 100,000 in 2011. After a significant decline since year 2000, the number of homicides in Mexico started to increase dramatically in 2007, soon after Calderon's administration took office in December 2006 and launched a military offensive against drug trafficking organizations (thorough an operation that deployed about 45,000 federal troops by 2011). Such a dramatic increase in the number of homicides between 2007 and 2011 was driven by a sharp increase in drug-related homicides, which increased at an annualized rate of 55.2 percent from 2007 to 2011, while non-drug-related homicides have actually decreased at an annualized rate of 3.6 percent over the same period. As a result, drug-related homicides, which represented 27.6 percent of total homicides in 2007, reached 71.8 percent in 2011.

The recent wave of drug-related violence observed in Mexico has concentrated in few territories. According to a recent report by the United Nations Office on Drugs and Crime (UNODC), four out of the 32 states in Mexico (which account for some 11 percent of the population) recorded 41 percent of the country's homicides in 2010, these states were Chihuahua, Sinaloa, Guerrero and Baja California (UNODC, 2011). Moreover, according to official data of the SNSP, 1,032 of Mexico's 2,456 municipalities (42 percent) have had presence of a drug cartel operating within their limits in 2011 (SNSP, 2011).

Figure 2: Total number of drug-related and non-drug related homicides in Mexico; 200-11



Source: SNSP, 2011, 2012 and 2014; Molzahn et al. 2013.

Law Enforcement in Mexico

In Mexico, different levels of government are constitutionally responsible for prosecuting different crimes. As a result, prosecution efforts that target crimes which are the sole responsibility of one level of the government are not necessarily supported by the other levels. Incentives under this scheme tend to be perverse and generate much judicial inefficiency, which ultimately impacts negatively the rates of conviction and thus reduces the marginal cost of violent crime. Organized crime, for example, is not a crime that is prosecuted at the local level, which means state and municipal governments will not prosecute drug traffickers unless they commit murder (which does constitute a crime at the municipal level).

Analogous to the judiciary system, the organization of police forces in Mexico is also complex. Each police force has a different level of jurisdiction and authority, and those levels often overlap. Federal law enforcement agencies are responsible for overseeing law enforcement across the entire country. In addition, there are several police organizations at the state, metropolitan and municipal level. The distinction between crimes investigated by the Federal and the State Judicial Police is not always clear. Most offenses come under the jurisdiction of state authorities. Drug dealing, crimes against the government, and offenses involving several jurisdictions are the responsibility of the Federal Police; while preventive and municipal police forces are mainly responsible for handling minor civil disturbances and traffic infractions. The latter point is particularly relevant for this paper since we will use per capita spending on local police as a control variable. This variable is likely not endogenous to the observed drug-related crime rate (although it may be to non-drug related homicides) since, as mentioned above, the spike in drug-related crime has been associated to the federal police and military intervention (and thus, should be closely linked to federal spending on police and security but not to local spending on citizen security).

4. Data

Data on Income, Poverty and Inequality at the Municipal Level

To construct income and inequality measures at the municipal level, we employ the small-area estimation methodology proposed by Elbers et al. 2003. The basic idea is to impute income to households in the Population Census (and Population Counts), using a model that predicts income from a household survey. Empirical evidence based on this method has proven to be precise when applied to data from nations like Ecuador, South Africa, Brazil, Panama, Madagascar and Nicaragua (see Elbers et al. 2003, Alderman et al. 2002, and Elbers et al. 2001). In addition, the small-area estimation methodology has key advantages as it benefits from the strengths of both household surveys and census and avoids their weaknesses. More specifically, whereas most household surveys are only representative at high levels of aggregation (e.g., national, regional, urban/rural), census and count data provide total coverage (universality).[6] Typically, census data provide the inputs when welfare indicators at low levels of aggregation, such as municipalities, are needed. In Mexico, both the Census and the Population Counts are representative at the municipality level, which is the unit of interest in this study.

However, the census has its limits. First, fewer variables are available compared to the more comprehensive household surveys. Second, one of the main weaknesses of this data and the most relevant for this analysis is the lack of information on income. Census data, not designed to comprehensively measure household income, provides an incomplete picture of the household's monetary circumstances, usually underreporting total income. Alternatively, household surveys such as the National Survey on Household Income and Expenditures (ENIGH), while representative only at the national and urban/rural level, are nevertheless designed to measure more precisely household income and expenditures.

The method consists of taking the household survey as a random sample of the total population (found in the census databases) and choosing the common variables between these sources. The distribution of the chosen variables is compared, looking for variables in which the sample mean is statistically equivalent to the population mean. The variables that are not rejected are used to model income with ordinary least-squares (OLS) regressions using household survey data. It is important to note that the coefficients obtained from the model cannot be economically interpreted—as some of them are endogenous—but they are still included to reduce prediction error. Finally, the parameters obtained from these income regressions are employed as predictors to generate the household income distribution in the census and count data.[7]

To construct the panel of poverty maps, we used available micro data from the following sources: (i) General Population Censuses of 1990, 2000 and 2010; (ii) the Population Count of 2005; and (iii) the National Survey on Household Income and Expenditure (ENIGH) 1992, 2000, 2005, and 2010. Following Elbers et al. 2003, to produce income measures at the municipal level, we paired the ENIGH of 1992 with the 1990 Population Census; the ENIGH of 2000 with the 2000 Population Census; the ENIGH of 2005 with the 2005 Population Count; and, the ENIGH 2010 with the 2010 Census. With the exception of the 1992 ENIGH and the 2000 Population Census, the remaining matches between ENIGHs and Censuses were collected at the same time of year—which ensures that every match represents the same socioeconomic context. As of 2014 there were 2,438 municipalities in Mexico, however, for the rest of this paper we consider 2,372 municipalities for

[6] Strictly speaking, Population Count data does not provide universal coverage as it consists in fact, of surveys not censuses. However, the sample size is large enough such that the data can be disaggregated to the municipal level and the level of precision of estimates is extremely high.

[7] In order to construct poverty maps for a twenty-year period, the analysis identified fifteen common variables between the ENIGH and the Census and Population Counts, which can be used to generate around 35 indicators to construct the necessary income models. These variables include dwelling characteristics, socio-demographic characteristics and asset ownership. Moreover, to increase precision in the estimators, around 50 municipality-specific indicators were chosen, including geographical and socioeconomic variables derived from various sources (e.g., the Territorial Integration System, ITER; the National Population Council, CONAPO; and the Ministry of Social Development, SEDESOL).

which there is comparable income, poverty and inequality data from the 1990-2010 panel of poverty maps (the 66 municipalities left out were created over the last twenty years).

Summary Statistics – Subnational Mean Income, Inequality and Poverty

As presented in Table 1, the summary statistics for the 2,372 municipalities followed over time show that mean real per capita income in Mexico in 2010 was lower than in 1990. This partly captures the effect of both the 1994-95 'Tequila Crisis', the 'dot-com bubble' of 1999-2001, and the most recent 2008-09 global financial crisis. Alternative measures of social welfare such as the food poverty[8] head count rate, the Gini coefficient, and literacy rates show marked improvements in 2010 (if compared to 1990). However, these positive trends are not as marked in magnitude with respect to the period that goes from 2005 to 2010.

Crime Indicators

Data on total number of homicides at the municipal level comes from official figures made public by the SNSP. The SNSP compiles information through an extensive collaborative taskforce involving several state and federal enforcement agencies.[9] Data on total homicides at the municipal level is available for the whole period under study; while monthly figures on drug and non-drug related crimes have been publicly released since 2006. In the analysis that follows, for each municipality, we have collapsed each of the crime variables available (total homicides rate, drug and non-drug related homicides) on a yearly basis.

Other Sources of Municipal Level Data

We have also gathered data on aggregate figures of public expenditures, literacy rates, and police expenditures at the municipal level in Mexico. The data on public expenditures was obtained from the State and Municipal System of Databases (SIMBAD) produced by the National Institute of Statistics, Geography, and Information (INEGI). The data on literacy rates (our proxy for human capital) is also obtained from public figures made available by INEGI, as is the data on public spending on police.

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[8] The food poverty line is defined by the National Council for the Evaluation of Social Development Policy (*Consejo Nacional de Evaluación de la Política de Desarrollo Social*, CONEVAL), as lacking sufficient income to acquire a basic food basket. The Council presents income poverty estimations at the national level and in the rural and urban sectors using information generated by the National Statistics and Geography Institute (INEGI).

[9] As described by Molzahn et al. 2012, the Center for Investigation and National Security (CISEN), the National Center for Information, Analysis and Planning to Fight Crime (CENAPI) within the Office of the Federal Attorney General (PGR), the Public Security Secretariat (SSP), Secretary of National Defense (SEDENA), the Secretary of the Navy (SEMAR), and the Secretary of the Interior (Gobernacion) are the institutions that participate in this collaborative effort.

5. Estimation Strategy

The relationship between income inequality and crime can be described by the following equation:

$$y_{it} = \beta(Gini)_{it} + X_{it} \cdot \delta + \varepsilon_{it} \qquad where\ \varepsilon_{it} = \mu_i + \omega_{it} \tag{1}$$

Where *i* indexes a municipality in Census/Count year *t, y* is a local crime rate indicator such as total murders per 100,000 inhabitants, *Gini* is the Gini coefficient at the municipality level, and the coefficient β indicates the estimated effect of income inequality on local crime rate. X contains a set of time-varying municipality characteristics, such as the share of the population that is poor, the percentage of rural households, local public expenditures per capita, police expenditures per capita and median household income. The term ε_{it} captures the unobserved determinant of local crime rates, which depends on a permanent component μ_i and a transitory component ω_{it}.

Pooling four cross-sectional data from 1990, 2000, 2005 and 2010 for each municipality, we estimate:

$$\Delta y_{it} = \beta(\Delta Gini)_{it} + X_{it} \cdot \delta + \Delta\varepsilon_{it} \tag{2}$$

This first-difference specification absorbs the permanent component of the error term (μ_i). The coefficient of interest (β) indicates the relationship between changes in the Gini coefficient and changes in crime rates within a municipality over time, holding constant changes in median income and basic demographics.

Equation (2) is not sufficient to establish a causal relationship between income inequality and crime. The income distribution may affect crime through a number of channels such as lower social capital, higher returns to criminal activity, low mobility, higher distress, etc. However, higher crime rates may affect local inequality by diminishing the stock of physical capital and development of human capital, by raising segregation and eroding social capital, by affecting the capacity of local governments and economic activity and by increasing the incentives to migrate to another municipality.

To mitigate concerns about this form of reverse causality, we construct an instrumental variable that is correlated with changes in local inequality but that is not associated with changes in local crime rates. Specifically, we follow Boustan et al. (2012) and predict the income distribution of a municipality based on the area's initial income distribution and national patterns of income growth; we then use the Gini coefficient for this predicted distribution as an instrument for the actual Gini coefficient.

In particular, we start with the initial (1990) average household income by *local* decile and municipality. We then estimate to which *national* percentile of the income distribution each *local* income decile belongs to in the initial year. For example, a household in the tenth (first) decile of a poor (rich) municipality might belong to the first (ninetieth) percentile at the national income distribution. Then, we allow the income of each local decile to grow over time as the income of its corresponding national percentile. By design, this instrument cannot be influenced by local factors such as the homicide rate or regional migration; rather, it isolates the component of change in the local income distribution (welfare variables) that is driven by national trends, such as changes in the return to skills and labor market institutions. In sum, this instrument allow us to isolate the change in the local income that is driven by national shifts and so, allows us to build 'counterfactual' welfare indicators, which should be correlated with municipal welfare indicators but not with local homicide rates or any other changes at the municipality level.

The instrumental variable approach will also help mitigate another potential source of bias. As the Gini coefficients at the local level were estimated using the poverty-mapping methodology (Elbers et al. 2003), they could be affected by measurement error, which may introduce the so-called *attenuation bias* in the OLS estimates. Since most of the time variation exhibited by our instrumental variable comes from national trends in the distribution of income, this helps mitigate measurement error biases in our municipal level income measures.

6. Results

A naïve OLS regression of equation (2), without addressing the reverse causality problem between income inequality and crime, leads one to conclude that higher inequality deters crime (see Table 2). In other words, increasing income inequality would be associated with lower crime rates in Mexican municipalities. According to the first column, a one-point increase in the Gini coefficient between 2006 and 2010 would be associated with a decrease of one drug-related murder per 100,000 inhabitants. That result holds in sign but differs in magnitude across all of our specifications. The main substantive conclusion, however, remains unchanged: i.e., increasing income inequality is correlated with lower crime rates, a counterintuitive result when compared with our hypothesized effect.

Several channels might contribute to this negative relationship between inequality and crime. For instance, if an increase in the crime rate within a municipality fosters the out-migration of richer households, then inequality might decrease as those households with less economic opportunities stay behind. In fact, there is empirical evidence that the increasing crime rates during this period have significantly raised geographic mobility among Mexican households. Rios (2013) estimates that a total of 264,693 individuals have migrated fearing organized crime activities in Mexico between 2005 and 2010. In addition, the paper presents anecdotal evidence whereby a significant number of these migrants do not belong to the lower part of the income distribution. For instance, while total immigration from Mexico to the United States declined during this period, the number of investor visas to Mexican nationals increased by 300 percent from 2000-2005 to 2005-2010.

Accordingly, a second mechanism that may be driving the negative correlation between inequality and crime is that increasing crime rates might depress home values and thereby affect the wealth and incomes of homeowners and real estate holders who do not move out. As a matter of fact, Rios

(2013) shows that the number of vacant dwellings in Mexican border cities is quite high and correlates strongly with the rates of drug-related homicides.

To identify the causal effect of inequality on crime, we estimate a 2SLS model. Table 3 shows the results of the first stage equation i.e., regressing the Gini coefficient using predicted inequality as the main explanatory variable. In Table 3, and in the rest of the 2SLS, we compute the instrumental variable using 1990 as the initial year for the 1990-2010 set of estimates, while we use 2000 as the initial year for the 2000-2010 and 2005-2010 estimates. The relationship between the predicted and actual Gini coefficients is strong and positive. In particular, the coefficient is close to 1 and its standard error is very low. The F-statistic of excluded instruments is equal to 97.53, 71.92 and 16.98 in 1990-2010, 2000-2010 and 2005-2010, respectively, all of them surpassing the conventional threshold for a strong instrument (see Stock and Yogo, 2005).

Table 4 shows our Two Stage Least Squares (2SLS) findings. Overall, our results show that for the 1990-2010 period, an increase of one point in inequality is associated with an increase of about 0.5 homicides per 100,000 inhabitants. However, this effect is substantially higher for the 2005-2010 period, where an increase of one point in the Gini Coefficient is associated with an increase of nearly six homicides. Moreover, this effect is even larger if we focus solely on drug-related crimes, where an increase in the Gini coefficient of about one point is associated with an increase of more than 10 deaths. These results are a sharp contrast with our OLS estimates, suggesting that income inequality has indeed had a significant effect on drug-related murders between 2005 and 2010. The estimates are quite large in magnitude when compared to the actual changes in crime rates during this period: the number of drug-related deaths per 100,000 inhabitants increased by about 10 deaths between 2005 and 2010 in Mexico. In other words, changes in inequality within municipalities were significant at shaping the geography of drug-related crime rates during Mexico's Drug War. It is important to mention that between 2005 and 2010, many municipalities (78 percent of them) witnessed a decrease in inequality, a pattern that was also observed at the national level. In this context, our results imply that if Mexico had not experienced such improvements in equality during this period, the increase in drug-related crimes might have been even more dramatic.

We do not find evidence that increasing inequality has had any effect on non-drug related crimes between 2006 and 2010, which shows that the positive effects found on the total homicide rate are driven by drug-related crimes. In other words, the increasing social tensions and pecuniary incentives for criminal activity associated with inequality did not seem to drive the geographic pattern of non-drug related crimes after 2006. At the same time, the effect of inequality on the total homicide rate was significant but substantially smaller when considering the period between the years 1990 and 2010. This result highlights the uniqueness of the Mexican situation between 2005 and 2010 as an experiment where the drop in the cost of criminal behavior facilitated the induction of individuals to the troops of drug-trafficking organizations.

It is important to mention that these models control for changes in poverty, thereby the estimated effect of inequality is mostly driven by changes in the upper portion of the income distribution. That is, the estimated positive effects of inequality on crime are more likely to stem from municipalities where rich households are becoming richer. Table 4 also shows that larger literate populations are associated with significantly lower crime rates across all specifications. At the same time, municipalities with higher levels of public expenditures have experienced lower crime rates (although the coefficients are not always significant).

Robustness Checks

To check the robustness of the main results presented above (Table 4), we employ a variety of other specifications. The first robustness exercise is to exclude outliers in our inequality measure, the Gini coefficient. To do so we remove those municipalities where the Gini coefficient falls within the following two criteria: 1. It is below the 5th percentile of the Gini coefficient distribution across municipalities, and 2. It exceeds the 95th percentile of the Gini coefficient distribution. As it can be noted, the results in Table 5 are similar in the order of magnitude and significance to the ones presented in Table 4. The second robustness check was carried out by eliminating from the sample those municipalities whose inequality measures are less precise. Specifically, we ranked all municipalities using the standard errors associated with the Gini coefficients estimated with the poverty map methodology described in the data section, and eliminated the top 10 percent. As Table A2 shows, the coefficients still have the expected sign and are statistically significant, but they are slightly smaller in magnitude.

In Mexico, the Technical Committee on Poverty Measurement adopted three monetary poverty measures since 2002: Food Poverty, Capabilities Poverty, and Assets Poverty (these measures will be discontinued starting in 2014). The results presented in Table 4 use food poverty—the most restrictive monetary poverty indicator of the three as it measures poverty as the household's lack of resources to afford a minimum basic diet. Therefore, to show that our results are still robust, we replace our poverty measure by the two less restrictive ones.[10] Table 6 presents the results if we use the Capabilities Poverty rates instead of the Food Poverty ones. As shown, the main results remain unchanged in terms of magnitude and significance. If we use the Asset Poverty rates instead (Table 7), we find a similar effect, although larger in terms of magnitude. For example, a unit increase in inequality increases the total number of homicides by more than 6 deaths. In the case of drug-related homicides a unit increase in inequality now leads to more than 13 deaths (instead of 10 when using Food Poverty).

Table 10 shows the estimates of a model that includes an interaction between the change in the Gini coefficient and the level of spending on police, to explore the existence of heterogeneous effects of inequality across different levels of spending. Unfortunately, municipal police spending is only available for 501 observations during this period, thereby our sample is significantly reduced. Under this specification, the parameter associated with the Gini coefficient is still positive but no longer

[10] Capacities poverty is defined as the lack of resources within a household to afford a minimum diet, education and health expenses. Assets poverty expands the notion of capabilities poverty to include households that cannot afford clothing, housing, energy, and transportation expenses.

statistically significant. However, the parameter associated with the interaction between the Gini coefficient and spending on police is negative and statistically significant, suggesting that the effect of inequality on crime was partially mitigated in municipalities with higher levels of spending.

Finally, since our instrumental variable depends on the initial levels of inequality, we estimate an additional specification that controls for the level of the Gini coefficient at the beginning of each period. Table 11 shows that the effect of the Gini coefficient on drug-related crimes is statistically significant and larger in magnitude than under our baseline results. These estimates suggest that our main results are not driven by the initial levels of inequality of Mexican municipalities.[11]

Effects in Urban and Rural Areas

Scholars have shown that crime rates tend to be higher in large cities than in rural or small urban areas of the United States because the pecuniary benefits for crime are higher in the former than in the latter (Glaeser and Sacerdote, 1996). At the same time, non-pecuniary factors such as lower arrest probabilities and different family structures in large cities also tend to explain a large share of the crime rate gap across these areas; and, at the same time, this share varies by type of crime. Guerrero (2011) points out that drug-related organizations in Mexico have broadened their scope of activities to other violent crimes (e.g., kidnapping, extortion, and vehicle theft), which in many cases are associated with increases in the homicide rate. This fact together with the lower costs associated with criminal activity during Mexico's Drug War imply that the effect of inequality on crime may have been different across urban and rural municipalities, since the change in the costs and benefits may have differed across areas as well.

Tables 8 and 9 present our results broken down by urban and rural municipalities.[12] If we focus just on rural municipalities, the statistical significance of our main findings disappears across specifications (see Table 8), although it increases in magnitude. When focusing on urban municipalities, Table 9 shows that higher levels of inequality increased both drug and non-drug related crimes throughout the complete period from 1990 to 2010. In particular, between 2006 and 2010, an increment of one point in the Gini coefficient increased drug and non-drug related homicides by about five and two deaths per 100,000 inhabitants, respectively. The fact that the main results are driven by urban municipalities is consistent with the effect of increasing inequality (and the associated increase in the expected benefits of criminal activity) on crime rates being larger in areas where arrest probabilities are lower and where the pecuniary benefits are already at a higher level.

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[11] We also estimated a specification using the log of the crime rate instead of its levels. Table A1 shows that the results are still consistent with those of our preferred specification in Table 4.

[12] Urban municipalities are defined in this paper according to the National Population Council (CONAPO) definition of urban areas. In that sense, a municipality with more than 15,000 inhabitants will be considered urban; and a municipality with less than 15,000 will be considered a urban (or semi-urban) area.

7. Concluding Remarks

The effect of inequality on crime has been empirically addressed by many scholars but with mixed results and mostly for developed economies. This paper attempts to estimate the effect of income inequality on crime in a unique context: Mexico's Drug War. During this period, drug-trafficking organizations multiplied and expanded geographically across the country, facilitating the incorporation of individuals to criminal activities. We exploit a rich data set containing within-country variation in inequality and crime rates for the more than 2,000 Mexican municipalities covering a period of 20 years. We also use an instrumental variable for inequality that tackles problems of reverse causality and omitted variables, which would introduce biases of this effect on OLS estimates.

Our results show that for the period that goes from 2005 to 2010, an increment of one point in our income inequality measure (the Gini coefficient) represents an increase of more than 6 homicides per 100,000 inhabitants across Mexican municipalities. Moreover, when we differentiate between different types of crimes, we find that the effect is even larger for drug-related crimes, i.e., an increment of one point in the Gini coefficient translates into an increase of more than 10 drug-related homicides per 100,000 inhabitants across Mexican municipalities. The results are large when compared to the overall increase in crime rates during this period in Mexico and are robust across different specifications. Our results imply that if Mexico had not experienced such improvements in equality during this period, the increase in drug-related crimes might have been even more dramatic. On the other hand, we find that the effect of an increase in the Gini coefficient on crime rates was substantially smaller when considering the complete period between the years 1990 and 2010. This highlights the fact that it is the combination of lower costs (associated with the expansion of drug gangs) and rising pecuniary benefits of criminal activity (associated with increasing inequality) that has a large impact on crime rates.

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Table 1. Descriptive Statistics

Variable	1990 Mean	1990 Std. Dev.	2000 Mean	2000 Std. Dev.
Real Income[1]	18363.31	8890.44	16657.37	9838.59
Gini Coefficient[1]	0.43	0.06	0.38	0.06
Food Poverty Headcount[1]	0.42	0.21	0.45	0.25
Share of Rural Population	0.89	0.26	0.87	0.28
Police Expenditure			187.98	69.97
Public Expenditure	592.46	782.29	1498.23	1303.93
Literacy Rate	0.77	0.15	0.81	0.12
Total Population[2]	33913.10	100515.40	40395.87	120041.60
No. Observations	2,372		2,372	

Variable	2005 Mean	2005 Std. Dev.	2010 Mean	2010 Std. Dev.
Real Income [1]	17,971.46	9,538.98	17,614.54	9,361.99
Gini Coefficient[1]	0.38	0.05	0.34	0.04
Food Poverty Headcount[1]	0.38	0.22	0.39	0.24
Share of Rural Population	0.87	0.28	0.86	0.29
Police Expenditure	182.46	68.60	250.14	90.84
Public Expenditure	2,324.52	1,757.12	3,037.27	2,267.26
Literacy Rate	0.83	0.11	0.86	0.10
Total Population[2]	42,700.54	127,528.60	45,666.65	130,964.00
No. Observations	2,372		2,372	

Source: [1]Author's own calculations using the ENIGH, Population Census and Population counts. [2] Consejo Nacional de Población CONAPO. All monetary figures are in per capita and real terms terms as August of 2010.

Table 2: OLS Estimates

	Drug related crimes	Non-drug related crimes	Homicide Rate		
	2006-2010	**2006-2010**	**1990-2010**	**2000-2010**	**2005-2010**
Gini	-104.029**	-31.412***	-10.736*	-14.947*	-60.399***
	(50.041)	(8.039)	(6.328)	(8.458)	(20.067)
Log Median Income	15.031	-0.383	3.258	-1.261	9.823
	(40.042)	(6.608)	(5.137)	(6.932)	(13.318)
Poverty	-2.345	-4.502	2.906	-13.026	3.953
	(71.774)	(11.024)	(9.316)	(12.132)	(22.591)
% Rural Population	-18.930	1.130	-0.054	-0.948	-6.686
	(19.360)	(3.975)	(3.238)	(3.857)	(6.526)
Log Public Expenditures	-9.006*	-1.255	-3.541***	-2.859***	-9.906***
	(5.046)	(1.453)	(0.899)	(0.751)	(2.180)
Log Literate Population	-177.987***	-4.706*	-20.305***	-28.913***	-72.843***
	(50.462)	(2.598)	(4.804)	(10.166)	(22.857)
Dummy Year 2000	(dropped)	(dropped)	-13.288**		
			(5.293)		
Dummy Year 2005			-9.300***	-10.518***	
			(1.076)	(1.312)	
Constant	38.912***	6.802***	10.885***	13.065***	16.956***
	(14.281)	(1.841)	(1.808)	(2.574)	(4.135)
Number of observations	1,872	1,872	5,991	3,839	1,872
R2	0.063	0.015	0.056	0.046	0.061

Dependent Variable: Difference in Crime Rates.

Robust Std. Errors within parentheses

All regressions are weighted by population size.

All monetary measures are expressed in real terms as August of 2010.

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 3: First Stage Regressions

	Gini 1990-2010	Gini 2000-2010	Gini 2005-2010
Predicted Gini - Instrument	1.360***	0.910***	0.864***
	(0.082)	(0.066)	(0.262)
Log Median Income	0.123***	0.085***	0.080***
	(0.013)	(0.015)	(0.018)
Poverty	0.233***	0.214***	0.207***
	(0.026)	(0.030)	(0.034)
% Rural Population	0.059***	0.060***	0.061***
	(0.009)	(0.010)	(0.012)
Log Public Expenditures	0.001	0.004	0.016***
	(0.002)	(0.003)	(0.004)
Log Literate Population	-0.003	-0.002	-0.010
	(0.005)	(0.009)	(0.012)
Dummy Year 2000	-0.012		
	(0.016)		
Dummy Year 2005	0.044***	0.127***	
	(0.002)	(0.007)	
Constant	-0.053***	-0.052***	-0.053***
	(0.004)	(0.004)	(0.005)
Number of observations	5,991	3,839	1,872
R2	0.196	0.193	0.072

Dependent Variable: Difference in Gini.

Robust Std. Errors within parentheses

All regressions are weighted by population size.

All monetary measures are expressed in real terms as August of 2010.

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 4: 2SLS Estimates					
	Drug related crimes	**Non-drug related crimes**	**Homicide Rate**		
	2006-2010	**2006-2010**	**1990-2010**	**2000-2010**	**2005-2010**
Gini	1,058.810**	40.284	51.097**	32.321	619.559**
	(528.085)	(128.460)	(21.938)	(21.316)	(295.886)
Log Median Income	-73.919	-5.207	-4.260	-5.341	-41.809
	(57.650)	(10.622)	(5.559)	(7.475)	(25.690)
Poverty	-239.541*	-14.212	-10.450	-22.345*	-133.861**
	(128.975)	(27.078)	(10.097)	(13.462)	(62.181)
% Rural Population	-92.172**	-1.873	-3.453	-4.049	-49.374**
	(42.533)	(8.873)	(3.545)	(4.363)	(21.096)
Log Public Expenditures	-27.488**	-2.575	-3.502***	-3.409***	-20.720***
	(10.975)	(2.259)	(0.903)	(0.822)	(6.657)
Log Literate Population	-168.750***	-3.112	-20.840***	-28.954***	-67.556***
	(52.426)	(3.717)	(4.875)	(10.242)	(25.227)
Dummy Year 2005			-5.765		
			(5.681)		
Dummy Year 2010			-12.215***	-12.680***	
			(1.634)	(1.780)	
Constant	115.722***	3.567	15.559***	16.314***	61.840***
	(40.756)	(8.501)	(2.525)	(3.290)	(20.886)
Number of observations	1,872	1,872	5,991	3,839	1,872

Dependent Variable: Difference in Crime Rates.

Robust Std. Errors within parentheses

All regressions are weighted by population size.

All monetary measures are expressed in real terms as August of 2010.

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 5: 2SLS Estimates trimming for outliers in Inequality (High Inequality)					
	Drug related crimes	**Non-drug related crimes**	**Homicide Rate**		
	2006-2010	**2006-2010**	**1990-2010**	**2000-2010**	**2005-2010**
Gini	1,043.106**	13.248	51.989**	32.919*	606.754**
	(426.121)	(107.186)	(23.188)	(19.350)	(240.420)
Log Median Income	-66.243	-3.161	-3.344	-2.959	-37.118
	(55.037)	(9.097)	(6.298)	(8.528)	(23.312)
Poverty	-232.327**	-8.661	-10.482	-19.136	-129.282**
	(113.503)	(22.894)	(11.397)	(15.055)	(52.420)
% Rural Population	-87.655**	-0.538	-2.788	-1.983	-45.814***
	(36.845)	(7.461)	(3.713)	(4.375)	(17.604)
Log Public Expenditures	-24.421***	-1.968	-3.882***	-3.812***	-18.989***
	(9.337)	(1.735)	(0.970)	(0.864)	(5.369)
Log Literate Population	-184.211***	-3.707	-24.841***	-32.910***	-74.047***
	(58.610)	(3.828)	(5.451)	(11.504)	(27.613)
Dummy Year 2005			-6.479		
			(6.439)		
Dummy Year 2010			-12.674***	-13.039***	
			(1.741)	(1.820)	
Constant	117.206***	1.868	16.386***	16.714***	62.005***
	(34.576)	(7.191)	(2.770)	(3.555)	(17.471)
Number of observations	1,710	1,710	5,424	3,480	1,710

Dependent Variable: Difference in Crime Rates.

Robust Std. Errors within parentheses

All regressions are weighted by population size.

All monetary measures are expressed in real terms as August of 2010.

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 6: 2SLS Estimates using Alternative Poverty Measures: Capabilities Poverty

	Drug related crimes	**Non-drug related crimes**		**Homicide Rate**	
	2006-2010	**2006-2010**	**1990-2010**	**2000-2010**	**2005-2010**
Gini	1,057.623**	43.459	51.044**	43.771*	631.768**
	(531.632)	(133.220)	(22.281)	(24.080)	(302.764)
Log Median Income	-54.692	-2.472	-3.509	-4.970	-24.741
	(51.204)	(6.966)	(5.090)	(6.234)	(20.791)
Capacities Poverty	-189.343*	-7.988	-8.891	-21.692*	-92.938**
	(105.689)	(17.612)	(9.360)	(11.363)	(46.601)
% Rural Population	-95.016**	-1.692	-3.501	-5.043	-49.577**
	(43.810)	(8.729)	(3.555)	(4.553)	(21.487)
Log Public Expenditures	-30.863**	-2.886	-3.515***	-3.500***	-23.045***
	(12.095)	(2.724)	(0.896)	(0.825)	(7.496)
Log Literate Population	-175.220***	-3.635	-20.934***	-29.064***	-71.725***
	(53.518)	(3.521)	(4.883)	(10.246)	(25.462)
Dummy Year 2005			-6.616		
			(5.108)		
Dummy Year 2010			-12.235***	-13.281***	
			(1.628)	(1.903)	
Constant	113.860***	3.212	15.442***	16.902***	59.829***
	(39.347)	(7.960)	(2.403)	(3.365)	(19.997)
Number of observations	1,872	1,872	5,991	3,839	1,872

Dependent Variable: Difference in Crime Rates.

Robust Std. Errors within parentheses

All regressions are weighted by population size.

All monetary measures are expressed in real terms as August of 2010.

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 7: 2SLS Estimates using Alternative Poverty Measures: Assets Poverty					
	Drug related crimes	**Non-drug related crimes**	**Homicide Rate**		
	2006-2010	**2006-2010**	**1990-2010**	**2000-2010**	**2005-2010**
Gini	1,376.323*	65.949	53.605**	38.503**	823.651*
	(782.888)	(178.230)	(24.048)	(17.043)	(454.622)
Log Median Income	109.765	9.461	2.254	4.530	75.561*
	(72.808)	(18.070)	(4.164)	(3.515)	(45.910)
Patrimonial Poverty	160.083	17.948	4.562	-1.340	122.455
	(141.041)	(34.833)	(11.075)	(10.301)	(87.470)
% Rural Population	-43.462	2.662	-1.398	-1.801	-15.730
	(30.607)	(4.508)	(3.535)	(4.251)	(16.276)
Log Public Expenditures	-37.257**	-3.151	-3.435***	-3.443***	-26.165***
	(15.814)	(3.256)	(0.901)	(0.808)	(9.738)
Log Literate Population	-181.301***	-3.748	-20.801***	-29.215***	-74.146***
	(58.714)	(3.516)	(4.910)	(10.309)	(28.117)
Dummy Year 2005			-12.548***		
			(4.155)		
Dummy Year 2010			-11.983***	-12.558***	
			(1.548)	(1.824)	
Constant	82.399***	0.683	13.835***	14.098***	39.676***
	(25.541)	(3.452)	(1.983)	(2.796)	(13.163)
Number of observations	1,872	1,872	5,991	3,839	1,872

Dependent Variable: Difference in Crime Rates.

Robust Std. Errors within parentheses

All regressions are weighted by population size.

All monetary measures are expressed in real terms as August of 2010.

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 8: 2SLS Estimates for Rural Municipalities					
	Drug related crimes	**Non-drug related crimes**	**Homicide Rate**		
	2006-2010	**2006-2010**	**1990-2010**	**2000-2010**	**2005-2010**
Gini	3,840.014	-530.011	36.488	35.005	814.461
	(4,764.188)	(789.926)	(33.642)	(33.230)	(1,205.466)
Log Median Income	-106.254	19.498	9.020	4.962	4.598
	(209.218)	(30.216)	(6.799)	(8.323)	(44.563)
Poverty	-379.192	55.447	16.018	-2.317	-36.305
	(539.843)	(83.100)	(12.686)	(15.234)	(121.996)
Log Public Expenditures	-95.642	8.999	-5.728***	-3.982***	-29.917
	(103.216)	(16.911)	(1.418)	(1.353)	(27.053)
Log Literate Population	-502.110**	18.848	-26.390***	-34.870*	-146.050*
	(252.926)	(31.598)	(8.470)	(20.666)	(87.309)
Dummy Year 2005			-7.647***		
			(2.502)		
Dummy Year 2010				9.707***	
				(3.538)	
Constant	294.068	-32.043	9.614***	1.618	63.985
	(286.574)	(46.017)	(3.486)	(2.500)	(72.835)
Number of observations	924	924	3,175	1,969	924

Dependent Variable: Difference in Crime Rates.

Robust Std. Errors within parentheses

All regressions are weighted by population size.

All monetary measures are expressed in real terms as August of 2010.

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 9: 2SLS Estimates for Urban Municipalities

	Drug related crimes	**Non-drug related crimes**	**Homicide Rate**		
	2006-2010	**2006-2010**	**1990-2010**	**2000-2010**	**2005-2010**
Gini	464.384**	194.830**	70.165***	35.240*	549.850***
	(199.158)	(77.833)	(27.154)	(18.894)	(207.254)
Log Median Income	-38.762	-20.181**	-18.176**	-13.830	-55.580**
	(23.850)	(10.054)	(7.850)	(11.140)	(26.602)
Poverty	-161.245***	-67.866**	-38.507***	-40.229**	-197.242***
	(57.818)	(26.398)	(14.135)	(19.347)	(64.778)
Log Public Expenditures	-8.811*	-1.907	-0.777	-2.129**	-8.117
	(5.040)	(2.089)	(0.867)	(0.939)	(5.127)
Log Literate Population	-31.955**	-0.096	-13.196***	-25.945***	-28.263**
	(14.024)	(4.229)	(3.167)	(4.800)	(13.764)
Dummy Year 2005			-19.383**		
			(8.986)		
Dummy Year 2010			-3.012	15.371***	
			(8.065)	(1.701)	
Constant	52.553***	15.029***	23.538**	4.886*	57.688***
	(14.037)	(5.656)	(10.914)	(2.959)	(15.082)
Number of observations	955	955	2,838	1,884	955

Dependent Variable: Difference in Crime Rates.

Robust Std. Errors within parentheses

All regressions are weighted by population size.

All monetary measures are expressed in real terms as August of 2010.

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 10: 2SLS Estimates including an Interaction Term between Inequality and Police Spending

	Drug related crimes	Non-drug related crimes	Homicide Rate
	2006-2010	2006-2010	2005-2010
Gini	1,729.048	300.598	2,659.832
	(1,516.075)	(386.151)	(1,990.223)
Log Median Income	14.864	-21.070	-77.185
	(78.075)	(19.886)	(102.493)
Poverty	-233.666	-86.376	-521.468
	(341.130)	(86.887)	(447.817)
% Rural Population	-103.776	-19.804	-182.631
	(116.156)	(29.585)	(152.484)
Log Public Expenditures	-4.434	-6.701	-23.749
	(19.928)	(5.076)	(26.161)
Log Literate Population	-335.064***	5.605	-272.489***
	(55.885)	(14.234)	(73.363)
Log Police Spending	63.277*	6.049	68.850
	(33.279)	(8.476)	(43.686)
Gini x Log Police Spending	-166.512*	-14.372	-176.291
	(85.925)	(21.885)	(112.798)
Dummy Year 2005			
Dummy Year 2010			
Constant	115.544	17.617	167.899
	(81.269)	(20.699)	(106.685)
Number of observations	501	501	501

Dependent Variable: Difference in Crime Rates.

Robust Std. Errors within parentheses

All regressions are weighted by population size.

All monetary measures are expressed in real terms as August of 2010.

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 11: 2SLS Estimates including Initial Levels in Inequality			
	Drug related crimes	**Non-drug related crimes**	**Homicide Rate**
	2006-2010	**2006-2010**	**2005-2010**
Gini	1,550.479**	100.348	906.295**
	(644.300)	(142.664)	(381.934)
Log Median Income	-112.393*	-9.907	-64.247**
	(61.789)	(11.467)	(32.301)
Poverty	-342.441**	-26.783	-193.871**
	(144.021)	(29.713)	(80.086)
% Rural Population	-119.181**	-5.173	-65.125**
	(49.222)	(9.511)	(27.062)
Log Public Expenditures	-35.626**	-3.569	-25.466***
	(14.072)	(2.524)	(8.506)
Log Literate Population	-161.902***	-2.275	-63.562**
	(54.023)	(3.824)	(26.275)
Dummy Year 2005			
Dummy Year 2010			
Initial Level in Inequality	105.153*	12.846	61.324**
	(54.641)	(8.132)	(28.264)
Constant	107.714**	2.589	57.170**
	(47.893)	(8.614)	(24.974)
Number of observations	1,872	1,872	1,872

Dependent Variable: Difference in Crime Rates.

Robust Std. Errors within parentheses

All regressions are weighted by population size.

All monetary measures are expressed in real terms as August of 2010.

Note: *** p<0.01, ** p<0.05, * p<0.1

Table A1: 2SLS Estimates - Log of Crime Rates

	Drug related crimes	Non-drug related crimes	Homicide Rate		
	2006-2010	2006-2010	1990-2010	2000-2010	2005-2010
Gini	20.588***	2.278	0.523***	0.564**	9.530***
	(7.183)	(1.806)	(0.198)	(0.280)	(3.497)
Log Median Income	-2.302***	-0.119	-0.074	-0.119*	-0.809***
	(0.652)	(0.169)	(0.050)	(0.068)	(0.308)
Poverty	-5.779***	-0.351	-0.137	-0.294**	-2.172***
	(1.571)	(0.414)	(0.096)	(0.131)	(0.748)
% Rural Population	-1.542***	-0.027	0.055	0.057	-0.627**
	(0.517)	(0.169)	(0.059)	(0.081)	(0.265)
Log Public Expenditures	-0.490***	-0.027	-0.028***	-0.047***	-0.260***
	(0.156)	(0.041)	(0.008)	(0.012)	(0.079)
Log Literate Population	-0.402	0.121*	0.005	-0.054	-0.214
	(0.291)	(0.066)	(0.027)	(0.046)	(0.142)
Dummy Year 2005			-0.061		
			(0.054)		
Dummy Year 2010			-0.150***	-0.157***	
			(0.015)	(0.019)	
Constant	2.040***	0.081	0.163***	0.191***	0.840***
	(0.478)	(0.127)	(0.021)	(0.030)	(0.231)
Number of observations	1,872	1,872	5,991	3,839	1,872

Dependent Variable: Difference in the log of the Crime Rates.

Robust Std. Errors within parentheses

All regressions are weighted by population size.

All monetary measures are expressed in real terms as August of 2010.

Note: *** p<0.01, ** p<0.05, * p<0.1

Table A2: 2SLS Estimates trimming for outliers in Inequality (High Std. Errors in Inequality from Poverty Maps)

	Drug related crimes	**Non-drug related crimes**	**Homicide Rate**		
	2006-2010	**2006-2010**	**1990-2010**	**2000-2010**	**2005-2010**
Gini	889.637**	3.558	36.981*	23.027	384.574*
	(434.946)	(109.958)	(20.555)	(22.264)	(198.719)
Log Median Income	-55.360	0.173	-2.497	-0.387	-15.492
	(60.473)	(8.446)	(5.254)	(6.691)	(18.198)
Poverty	-198.474	-2.560	-6.137	-12.196	-72.777*
	(127.864)	(21.969)	(9.460)	(12.095)	(42.819)
% Rural Population	-81.434**	1.016	-2.789	-2.646	-33.404**
	(39.686)	(7.730)	(3.486)	(4.249)	(15.383)
Log Public Expenditures	-22.731***	-1.785	-3.349***	-3.273***	-15.496***
	(8.698)	(1.869)	(0.891)	(0.844)	(4.531)
Log Literate Population	-173.010***	-2.267	-20.609***	-28.467***	-67.610***
	(56.210)	(3.869)	(5.137)	(10.856)	(25.612)
Dummy Year 2005			-6.987		
			(5.403)		
Dummy Year 2010			-10.700***	-11.305***	
			(1.586)	(1.770)	
Constant	102.506***	0.070	13.802***	13.888***	42.763***
	(37.573)	(6.898)	(2.498)	(3.156)	(14.610)
Number of observations	1,769	1,769	5,683	3,638	1,769

Dependent Variable: Difference in Crime Rates.

Robust Std. Errors within parentheses

All regressions are weighted by population size.

All monetary measures are expressed in real terms as August of 2010.

Note: *** p<0.01, ** p<0.05, * p<0.1