Journal of Development Economics 120 (2016) 128–143

Contents lists available at ScienceDirect

Journal of Development Economics

journal homepage: www.elsevier.com/locate/devec

Income inequality and violent crime: Evidence from Mexico's drug war☆

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ARTICLE INFO

Article history:
Received 8 September 2014
Received in revised form 16 December 2015
Accepted 22 December 2015
Available online 20 January 2016

Keywords:
Income inequality
Crime
Instrumental variables
Mexico

ABSTRACT

The goal of this paper is to examine the effect of inequality on crime rates in a unique context, Mexico's drug war. The analysis exploits an original dataset containing inequality and crime statistics on more than 2000 Mexican municipalities over a 20-year period. To uncover the causal effect of inequality on crime, we use an instrumental variable for the Gini coefficient that combines the initial income distribution at the municipality level with national trends. Our estimates indicate that a one-point increment in the Gini coefficient between 2007 and 2010 translates into an increase of more that 36% in the number of drug-related homicides per 100,000 inhabitants. The fact that the effect found during the drug war is substantially greater is likely caused by the rise in rents to be extracted through crime and an expansion in the employment opportunities in the illegal sector through the proliferation of drug trafficking organizations (DTOs), accompanied by a decline in legal job opportunities and a reduction in the probability of being caught given the resource constraints faced by the law enforcement system. Combined, the latter factors made the expected benefits of criminal activity shift in a socially undesirable direction after 2007.
Sector Board: Poverty (POV)

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 the topic finds that the effect is positive, 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, in the focus 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 in delving into this subject. For example, cross-country studies are usually biased because of measurement errors and problems of omitted variables, and they are also limited by small sample sizes. Reverse causality is a matter of concern because rising crime rates may also affect inequality by, for example, encouraging richer residents to move out of violent locations.

Neumayer (2005) points out that a focus on within-country variation could be a remedy to the difficulty of controlling for confounding factors at the country level and the small sample problem that arises in cross-country analysis. Nonetheless, even if these problems are addressed, the reverse causality problem remains. In this paper, we take a step forward by tackling the aforementioned challenges by focusing on within-country variations at the municipal level in violent crime and inequality in Mexico, and, by using the predicted income distribution of a municipality based on the initial income distribution of the local area and the national patterns of income growth, we construct an instrument (predicted Gini) for the observed Gini coefficient (Boustan et al., 2013).[1] This instrument, by construction, isolates the component of change in inequality that is driven by national trends and that is not influenced by local factors such as the homicide rate.

We focus our attention on Mexico because it represents a unique case among developing nations. First, in terms of violent crime rates,

☆ The authors would like to thank Alberto Diaz-Cayeros, Alan Fuchs, Beatriz Magaloni, Samuel Freije-Rodríguez, and seminar participants at Stanford University, Universidad Iberoamericana, the World Bank, and the 2014 Lacea Lames conference held at Universidade de São Paulo for their thoughtful comments and useful suggestions. Also, the authors would like to thank Eduardo Ortiz-Juarez, Daniel Valderrama and Robert Zimmerman for valuable contributions. The findings, interpretations, and conclusions in this paper are entirely those of the authors. They do not necessarily represent the view of the World Bank, its executive directors, or the countries they represent. The data and the supporting materials necessary to reproduce the results in the paper will be made available on the authors' webpages.

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[1] This paper uses the term violent crime throughout, but does not attempt to distinguish among the impacts of the types of violence or crime that do not involve homicide. The terms violence and crime describe different concepts. According to the World Health Organization, violence refers to the intentional use of physical force or power, threatened or actual, against oneself or another person or against a group or community that either results in or has a high likelihood of resulting in injury, death, psychological harm, or deprivation. Meanwhile, crime includes actions that may or may not include the use of force or injury on another person, for example, most property crimes such as theft, embezzlement, fraud, tax crimes, some forms of racketeering, and bribery.

http://dx.doi.org/10.1016/j.jdeveco.2015.12.004
0304-3878/

while the total rate of homicides in Mexico followed a downward pattern during 1990–2005, the picture has been totally different since December 2006 when the federal government launched a military offensive against drug trafficking organizations (DTOs) known as the drug war. After the start of this intervention, violent confrontations between competing DTOs and between official armed forces and DTOs became more frequent, and violent crime soared. For instance, in 2005, the total rate of homicides was close to 11 per 100,000 individuals; by 2010, it was 18.5 per 100,000 individuals according to data reported by the Technical Secretariat of Mexico's Sistema Nacional de Seguridad Publica (National Public Security System, SNSP), a federal entity within the Ministry of Interior (SNSP, 2014). In 2005, there were more than 7000 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 had raised the number of homicides not related to DTOs by a factor of more than three (Aguilar, 2012; Guerrero, 2011). To illustrate the economic implications of this phenomenon, losses to victims of crime were valued at US$12.9 billion in 2010 according to results of the 2011–2012 National Victimization Survey, and additional health costs reached US$619 million. This represents a total cost of US$13.5 billion (1.2% of Mexico's GDP) and would be equivalent to an annual tax of US$117 per capita.[2] Recent studies of the impact of Mexico's drug war have also documented the significant negative effects of violent crime on economic outcomes, such as the lack of growth among businesses, regional growth convergence, employment, and labor earnings (Dell, 2015; Enamorado et al., 2014; Robles et al., 2013; Velásquez, 2014).[3] These studies suggest that drug-related crime may be affecting the economy by increasing extortion and inducing the migration of individuals and firms to safer territories.

Second, while there have been major advances in reducing income inequality in Mexico over the last 15 years, with a decline from 0.547 to 0.475 in the Gini coefficient for the distribution of household per capita income (Lustig et al., 2013), there is heterogeneity across regions. Between 1990 and 2005, about 90% of the municipalities in Mexico registered a decline in income inequality, while, between 2005 and 2010, about 78% of the municipalities experienced a reduction in the Gini coefficient. Despite an overall drop 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 in which low-income mobility is a widespread problem (Cuesta et al., 2011).

Our results from linear regression models that do not account for reverse causality and omitted variables predict that, in the case of Mexico, a widening in inequality is linked to a decline in homicides. We argue that this result may be driven by the selective out-migration of richer residents to safer municipalities (consistent with the evidence in previous studies) 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, in the 2007–2010 period, an increase of 1 unit in the Gini coefficient (our income inequality measure) translates into a rise by more than six additional deaths per 100,000 individuals in the total homicide rate. Moreover, this effect is larger if we focus only on drug-related crimes: a one-unit increase in the Gini coefficient is associated with an increase of more than 10 deaths (or to an increase of 36% according to an alternative specification). In the case of non-drug-related homicides, we do not find any evidence suggesting that changes in inequality have played a role in determining these types of crimes during Mexico's drug war. We do find that inequality has increased non-drug-related crimes since 1990, but the effects are substantially smaller in magnitude. The results are unaffected by alternative specifications and different robustness checks.

These results contribute to a growing literature on the main drivers behind the upsurge in violent crime experienced since the start of Mexico's drug war. According to recent studies, there are three main lines of analysis on the causes of the large spike in homicide rates in Mexico: (1) tougher domestic drug enforcement policy (Dell, 2015; Durante and Gutierrez, 2013; Guerrero, 2011; Merino, 2011), (2) external shocks affecting the behavior of DTOs (Castillo et al., 2014; Dube et al., 2013; Hope, 2013), and (3) variations in socioeconomic factors (De Hoyos et al., 2015; Gomez and Merino, 2012; Osorio, 2012). To the best of our knowledge, we are the first to identify variations in socioeconomic factors as a causal effect of the upsurge in violent crime in Mexico, and this study complements previous descriptive reports on the links between poverty and crime in Mexico (Osorio, 2012; UNDP, 2013). Because we analyze differentiated homicide rates, this paper will also contribute to the literature by distinguishing whether the impact of income inequality on crime rates is more pronounced in common crime or drug-related crime.

The effect of greater inequality on crime can be understood in a cost–benefit framework in the style of Becker (1968). As discussed by Demombynes and Ozler (2005), the expected gains from criminal activity rise with the mean income at the local level. An increase in incomes at the top translates into higher mean incomes locally. However, higher inequality implies that a group of people is left at the bottom and that their expected gain from illegal activities expands. In the case presented in this paper, the increase in the rents to be extracted at the local level through activities related to DTOs is accompanied by an expansion in the employment opportunities in the illegal sector through the proliferation of DTOs, a decline in legal job opportunities caused by modest local economic conditions, and a reduction in the probability of being caught because of the resource constraints faced by the law enforcement system.[4] The combination of these effects means that criminal activity becomes a rational decision for a larger group of people. These more rational elements may then be reinforced by social disorder and losses in social capital, with feedback into the negative dynamics.

The rest of this paper proceeds as follows. Section 2 presents a literature review of the theoretical and empirical evidence that links inequality with crime and a succinct examination of the lines of analysis of the main causes of the upsurge in violent crime in Mexico. Section 3 offers an overview of medium- and long-run trends in subnational income inequality and violent crime, particularly since the start of

[2] According to information of the World Bank's Enterprise Surveys in 2012, 42.8% of Mexico's firms paid for private security, spending the equivalent of about 2.2% of their annual sales on these services. In addition, according to official numbers of the Ministry of Finance, the total budget assigned to civilian security and military agencies, criminal justice, and judicial institutions in 2012 was US$14.44 billion, approximately 6% of the total budget of the government of Mexico.

[3] Robles et al. (2013) study the effect of DTO-related homicides on economic activity (measured based on electricity consumption) and unemployment. They find that an increase of 10 homicides per 100,000 inhabitants generates a decrease of two or three percentage points in the proportion of people who are working. They suggest that drug-related crime may be affecting the economy by increasing extortion, inducing the migration of businesses and business owners to safer territories, and a decline in capital investment and in the creation of new businesses. Enamorado et al. (2014) document that municipalities with higher levels of drug-related crimes in 2007 grew at a slower pace between 2005 and 2010 than municipalities less affected by this shock. These results indicate that a rise of one standard deviation in the number of drug-related crimes in 2007 (approximately 18 homicides per 100,000 inhabitants) implies a decrease in municipal income growth of 0.20%. After taking into consideration endogenous migration, Velásquez (2014) presents evidence showing that increases in the homicide rate boost the probability that self-employed women will leave the labor market and reduce the number of hours they work. Dell (2015) shows that homicide rates and the diversions of economic activity associated with drug trafficking have negative impacts on informal sector earnings and female labor force participation, but finds no significant effect on formal sector wages and male labor force participation. Dell concludes that, while economic effects may be noisily estimated, they are consistent with qualitative evidence that DTOs extort informal sector producers through the protection racket.

[4] For example, De Hoyos et al. (2015) find an association between the share of unemployed young people (people who are neither attending school nor employed) and crime rates in Mexico, particularly in states located at the border between Mexico and the United States.

Mexico's drug war. Section 4 describes the 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 is constructed. Section 6 outlines our main findings. Section 7 concludes.

2. The literature on the links between income inequality and crime

The literature supplies two complementary theories for the identification of potential mechanisms through which income inequality may foster crime. First is the concept of criminal behavior as a cost–benefit calculation that was introduced in the economics literature by the seminal work of Becker (1968). 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. These calculations are influenced by the deterrence mechanisms and penalties put in place to prevent crime. According to this theory, inequality leads to crime by placing low-income individuals who have low returns from market activity in proximity to high-income individuals who have things that are worth taking (Kelly, 2000). In other words, even if poverty remains fixed, a larger income gap between the poor and the rich would lead to rising criminal behavior because the expected gains of criminal activity are related to the wealth and assets of the potential targets.

The second approach embodies the sociological theories of crime introduced by Merton (1938), who centers his attention on the emotional feelings that lead people to become delinquents. According to this theory, individuals low in the social structure are frustrated by their failure to attain the material attributes of success, and this failure is more galling when they are confronted by the success of those around them (Kelly, 2000). According to these theories, a poor individual would be more likely to become violent in a place where inequality is high when compared with a similar individual living in a more egalitarian society.[5]

Regardless of the mechanisms, whether rational calculation or emotional motivation, both theories strongly suggest that higher levels of inequality help boost crime, even after one controls for poverty levels. Many authors have tried to test these theories empirically, but have obtained mixed results. For example, Ehrlich (1973) finds that, in the United States in 1940–1970, inequality and income were positively correlated with property crimes (robbery, burglary, larceny, and auto theft) and violent crimes (murder and rape). Blau and Blau (1982) argue that economic inequality is at the root of violent crime in the United States. In their findings, the role of variables such as poverty in explaining crime is outweighed by the predictive power of inequality. In this same line of work, Kelly (2000) finds that, in urban areas in the United States, while inequality is not significantly correlated with property crime, it is actually the main driver of violent crime.

Fajnzylber et al. (2002b), in their analysis of data on homicides and robberies in a cross-section of industrialized and developing countries, find that inequality increases robberies (here, a proxy for property crimes) and homicides (a proxy for violence). Poveda (2011) finds that inequality has positive impacts on the homicide rates in seven major cities in Colombia. Similarly, using a sample of countries in the Organization for Economic Co-operation and Development and Central and South American countries, Nadanovsky and Cunha-Cruz (2009) find that less inequality is associated with lower homicide rates. Demombynes and Ozler (2005) find that greater inequality in South Africa is associated with higher rates of property crime and violent crime in neighborhoods.

Other studies have found opposite results for the effect of inequality on crime. Neumayer (2005) directly calls into question the results of Fajnzylber, Lederman, and Loayza (2002b), arguing that, by increasing the sample size of countries, inequality—measured by the Gini coefficient—is no longer statistically significant in predicting violent crime.[6] Moreover, Pridemore (2011) criticizes the large cross-country literature that studies the link between inequality and homicide rates because most of the literature fails to control for poverty rates, which is the most consistent predictor of area homicide rates in the empirical literature on the United States. Pridemore replicates previous cross-country studies that show a statistically significant relationship between inequality and homicides and finds that, if the models control for poverty rates, the relationship is no longer significant.

Using county-level data for the United States, Brush (2007) obtains mixed results in terms of the effect of income inequality on crime rates. Applying cross-sectional analysis, he finds that income inequality promotes crime, but, by centering his attention on a time series analysis, he finds that income inequality reduces crime. However, his time series analysis includes only two census years (1990 and 2000). Finally, in a recent study using state-level inequality data on the United States, Chintrakarn and Herzer (2012) find that inequality is negatively correlated with crime. Their explanation of this counterintuitive result is based on the idea that the greater the inequality in a state, the larger the demand for security services, which leads to a reduction in crime.

2.1. Violent crime and inequality in Mexico

There is a growing literature on the main drivers of the upsurge in violent crime experienced since the start of Mexico's drug war. Thus, Hope (2013) posits three main causes behind the large spike in homicide rates in recent years: (1) the domestic drug enforcement policy; (2) exogenous dynamics, including increases in the price of drugs, the expanded supply of guns, and the more frequent deportation of immigrants with a criminal record from the United States; and (3) variations in socioeconomic indicators.

Regarding the first line of analysis, recent empirical work by Dell (2015) and Durante and Gutierrez (2013), together with qualitative studies by Guerrero (2011) and Merino (2011), conclude that the primary cause of the upsurge in violence has been the government's drug enforcement policy. Durante and Gutierrez (2013) exploit a regression discontinuity design in close municipal elections to document how political alignment among neighboring municipalities in Mexico improves cooperation in crime prevention. Their results show that better intermunicipal coordination in drug enforcement policy decreases homicide rates by between 35 and 43%. Dell (2015) uses close municipal elections to estimate that there are 27 to 33 more drug-related homicides per 100,000 municipal inhabitants after a municipal mayor in a political party aligned with the federal government takes office. Merino (2011) estimates that the rate of homicides in Mexico between 2008 and 2009 would have been about 25% lower under a scenario not involving the deployment of official armed forces. Guerrero (2011) presents qualitative and descriptive evidence to show that government intervention has been the main cause of violent confrontations among DTOs.

The second line of analysis argues that exogenous factors have contributed to the significant increase in violent crime in Mexico since 2007. Castillo et al. (2014) find that supply shocks caused by greater enforcement of Colombia drug trafficking policies created an increase in the price of cocaine. This led to a rise in drug-related violence in Mexico because DTOs fought over the appropriation of the higher rents deriving from scarcer drugs.[7] They find that, in 2006–2010, the scarcity of cocaine accounted for 21.2% and 46.0%, respectively, of the increase in homicides and drug-related homicides in the north of Mexico. Dube et al. (2013) exploit the 2004 expiration of the U.S. federal assault weapons ban as a natural experiment to study the effect on gun supply

[5] Fajnzylber et al. (1998, 2002a, 2002b) and Whitworth (2012) are examples of recent empirical work presenting evidence supporting these concepts.

[6] Neumayer (2005) uses 59 countries in his sample. There are 45 countries in the sample of Fajnzylber et al. (2002b).

[7] Previously, Angrist and Kugler (2008) documented a similar phenomenon of an exogenous increase in the price of cocaine in rural districts in Colombia that generated violent events because of conflict over the additional rents.

in Mexican municipalities close to the border with Arizona, New Mexico, and Texas. They document a rise of at least 238 additional deaths annually in the area located within 100 miles of the entry ports to these three U.S. states. Hope (2013) hypothesizes that the firmer enforcement of immigration policy at the United States–Mexico border since 2001, combined with an expansion by 35% in the deportations of immigrants with a criminal record by the U.S. immigration authorities may have boosted crime rates in the border states in Mexico.

The third approach explaining the spike in violent crime in Mexico relies on variations in socioeconomic conditions. According to Hope (2013), although it is likely that socioeconomic factors had a direct impact on violence in Mexico between 2007 and 2011, these probably accelerated rather than generated the phenomenon. Evidence on the effects of socioeconomic indicators on violent crime since the start of the drug war is thin. Gomez and Merino (2012) document the lack of an impact of the rate of young adults who were neither enrolled in the education system nor working exercised on the variations in violent crime. De Hoyos et al. (2015) study the same phenomenon, but unlike Gomez and Merino, they exploit spatial heterogeneity to present evidence that a 1% increase in the share of unemployed male youth (ages 19 to 24) in a border state between 2007 and 2013 correlated with a rise of 2.8 homicides per 100,000 inhabitants. They conjecture that, as a result of the international financial crisis, young, relatively unskilled male adults traditionally employed in the manufacturing sector in the north of Mexico faced a significant reduction in the legal labor market in this sector, which increased the likelihood they would join DTOs. Osorio (2012) and the United Nations Development Program (UNDP, 2013) offer descriptive evidence about the relationship between violence and poverty in municipalities in Mexico, but ignore the role of inequality.

We expect the effect of inequality on organized crime to be reinforced in the context of Mexico's drug war. The literature shows that the proliferation of gangs tends to promote the propensity to commit crimes because they facilitate the access to the knowledge and logistics associated with criminal activities (Gatti et al., 2005; Thornberry et al., 1993; Zhang et al., 1999). Gangs also tend to lower the marginal cost of criminal behavior. The proliferation of gangs would thus have a greater impact on the incidence of crime in cities with high rates of inequality because any higher cost associated with crime is more likely to represent a binding constraint on criminal activity among individuals possessing fewer economic resources, while controlling for poverty. The splintering and geographical diffusion of DTOs during Mexico's drug war may have facilitated criminal behavior disproportionally in cities that became more unequal during the period. At the same time, the widening inequality associated with an expansion in the wealth of individuals who are already rich would also tend to exacerbate these effects by increasing the expected payoff from criminal activity. Thus, if the cost of crime decreases and the income differences between the poor and the rich become larger, the net benefits anticipated from criminal activities such as extortion, kidnapping, and theft would rise.

The literature shows that empirical evidence on the effects of inequality on crime is mixed. While some authors have presented suggestive evidence on the importance of socioeconomic factors in the spike in crime rates, our paper is the first to identify a causal effect between variations in socioeconomic factors and the crime phenomenon. Our paper overcomes many of the limitations of previous studies by focusing on within-country variation (and thereby a large number of observations), by controlling for changes in poverty (and thereby disentangling the effects of changes in the top from changes in the bottom of the income distribution) and by using an instrumental variable for changes in inequality.

3. Income inequality and crime in Mexico: some stylized facts

3.1. Trends in income inequality

Although income inequality measured by the Gini coefficient declined by about six points from 1996 to 2010, recent data show that this trend slowed in 2005–2010 and displayed a slight reversal between 2010 and 2012 (INEGI, 2013; Lustig et al., 2013). There was significant within-country variability across these same periods. Over the longer run (1990–2010), about 90% of the municipalities in Mexico were affected by a reduction in the Gini coefficient, while, over the medium run (2005–2010), about 73% of the municipalities showed a decline in inequality.

Charts a and b in Fig. 1 show the medium- and long-run changes in the Gini coefficient in municipalities with respect to the national average; the weighted average is −5.3 Gini points for 1990–2010 and −3.7 for 2005–2010. Between 1990 and 2010, about 67% of the more than 2000 municipalities in Mexico, representing about 49% of the total population, reduced the Gini coefficient more quickly than the national average, while 23% (33% of the total population) showed a narrowing in inequality over the same period, though at a lower rate than the national average; the remaining 10% (18% of the total population) experienced a widening in inequality. During the medium-run period of 2005–2010, about 50% of all municipalities exhibited a narrowing in inequality at a rate above the national average, and 28% showed a decline at a rate below the national average (53% and 28% of the total population, respectively), while 22% experienced a rise in the Gini coefficient (19% of the total population). These data confirm that, although income inequality narrowed in the majority of municipalities over both the medium and long run, income inequality widened in many municipalities, particularly in 2005–2010, overlapping with the drug war.[8]

3.2. 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 the SNSP (Fig. 2). These data correspond to a homicide rate of 13.7 per 100,000 population in 2000 and 19.8 per 100,000 in 2011. After a significant decline after 2000, the number of homicides started to increase dramatically in 2007, soon after the Calderon administration took office in December 2006 and launched a military offensive against DTOs through an operation that involved the deployment of about 45,000 federal troops by 2011. This dramatic rise in the number of homicides was driven by a jump in drug-related homicides, which increased at an annualized rate of 55.2% from 2007 to 2011, while non-drug-related homicides declined at an annualized rate of 3.6% over the same period. As a result, drug-related homicides, which represented 27.6% of total homicides in 2007, reached 71.8% in 2011.

The recent wave of drug-related violence in Mexico has been concentrated in a few territories. According to a recent report by the United Nations Office on Drugs and Crime (UNODC, 2011), 4 of the 32 states in Mexico—Baja California, Chihuahua, Guerrero, and Sinaloa, which account for around 11% of the population—recorded 41% of the country's homicides in 2010. Moreover, according to official data of the SNSP (2014), DTOs were active in 1032 of Mexico's 2456 municipalities (42%) in 2011.

3.3. Law enforcement

In Mexico, various levels of government are constitutionally responsible for prosecuting different crimes. As a result, the prosecution of crimes that are the sole responsibility of one level of government is not necessarily supported by the other levels of government. The incentives available under this scheme tend to be perverse and generate much judicial inefficiency, which ultimately impacts negatively the

[8] Fig. 1A in the online appendix presents changes in inequality that are similar to the ones shown in Fig. 1. The main difference is that Fig. 1A focuses on the variations in our instrument for inequality. The purpose of both figures is to show that actual and predicted changes in inequality are occurring across municipalities. We exploit these variations to identify our effect of interest, that is, the impact of inequality on crime.

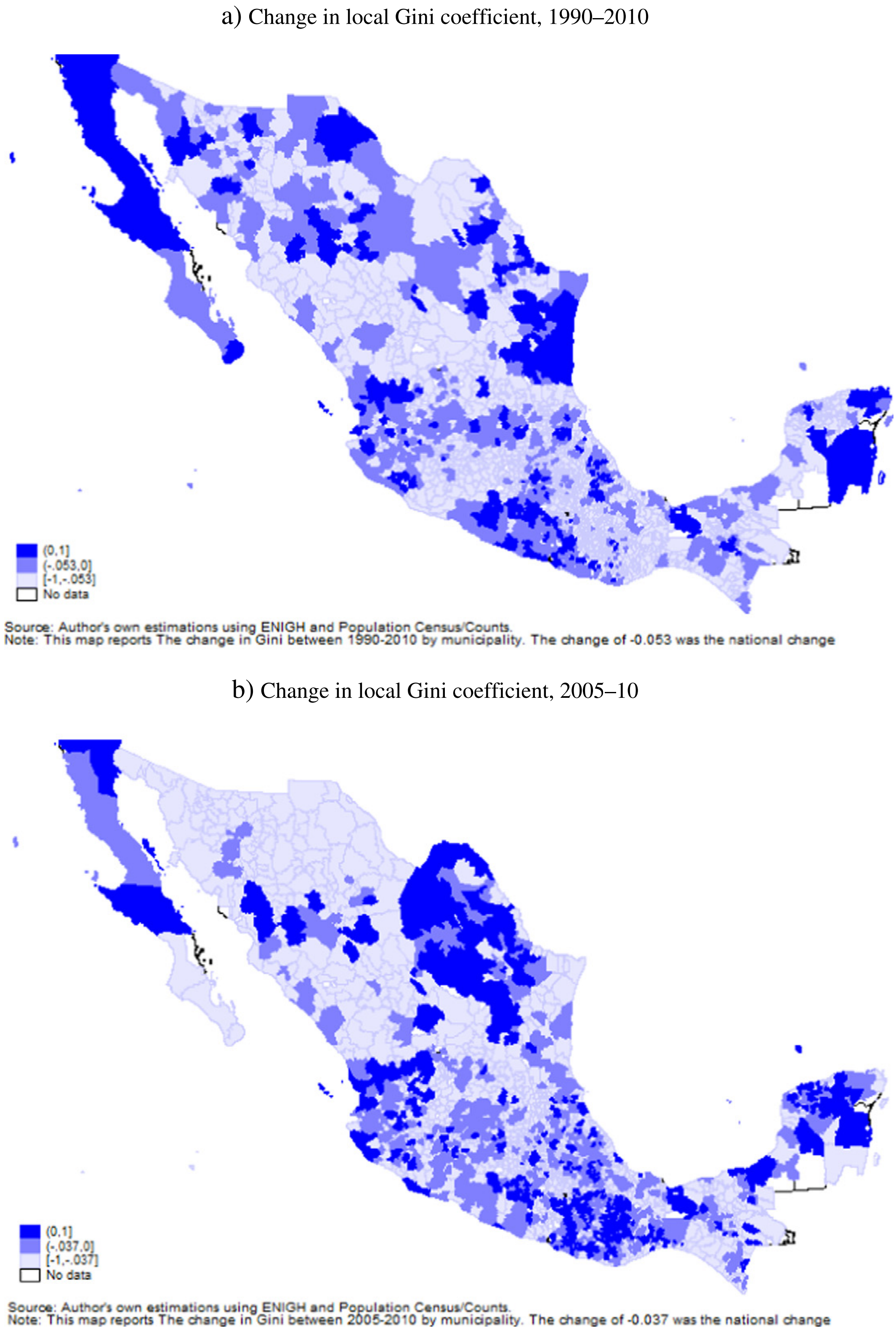

Fig. 1. Medium- and long-run variation in income inequality, municipalities vs. the national average, 1990–2010 and 2005–2010. a. Change in local Gini coefficient, 1990–2010. b. Change in local Gini coefficient, 2005–2010.

rates of conviction and thus reduces the marginal cost of violent crime. Organized crime, for example, is not prosecuted at the local level, which means municipal and state governments will not prosecute drug traffickers who have not committed a murder, which is not a prosecutable offense at the municipal level.

The organization of the police forces is also complex. Each police force has its own jurisdiction and authority, and these often overlap. Federal law enforcement agencies are responsible for overseeing law enforcement across the entire country. There are also several police organizations at the municipal, metropolitan, and state levels. The

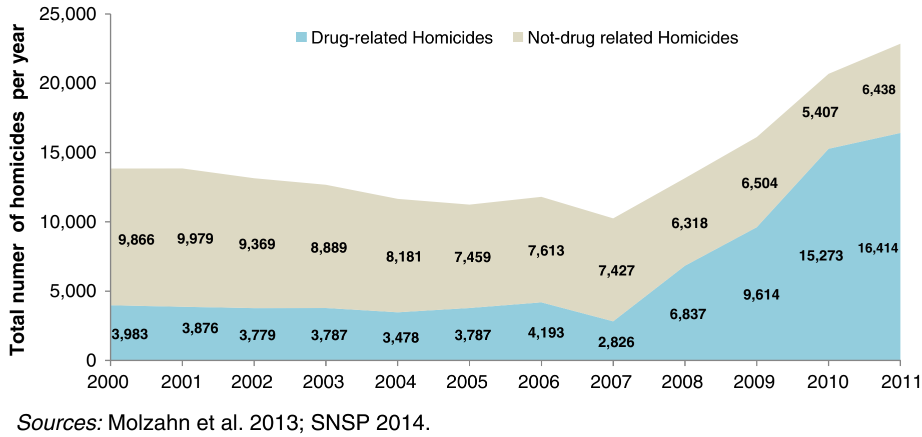

Fig. 2. Drug-related and non-drug-related homicides, Mexico, 2007–2011.
Sources: Molzahn et al. (2013) and SNSP, 2014.

distinction among 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. This is particularly relevant in this paper because 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 endogenous to non-drug-related homicides, because the spike in drug-related crime has been associated with the interventions of the federal police and military, and, thus, should be closely linked to federal spending on police and security, but not to local spending on citizen security.

4. Data

4.1. Data on income, poverty, and inequality in municipalities

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 if applied to data from nations such as Brazil, Ecuador, Madagascar, Nicaragua, Panama, and South Africa (Alderman et al., 2002; Elbers et al al., 2003; Ferreira et al., 2000). In addition, the small area estimation methodology has key advantages because it benefits from the strengths of both household surveys and the census, while avoiding their weaknesses. More specifically, whereas most household surveys are only representative at high levels of aggregation (for example, urban and rural, regional, and national), census and population count data provide total coverage (universality).[9] Typically, census data provide the inputs if welfare indicators at low levels of aggregation, such as municipalities, are needed. In Mexico, both the census and the population counts are representative of municipalities, which is the unit of interest in our study.

However, the census has limitations. First, fewer variables are available compared with the more comprehensive household surveys. Second, one of the main weaknesses of these data and the most relevant for this analysis is the lack of information on income. Because they are not designed to measure household income comprehensively, census data supply an incomplete picture of the monetary circumstances of households and usually underreport total income. Alternatively, household surveys such as the Household Income and Expenditure Survey (Encuesta Nacional de Ingresos y Gastos del Hogar, ENIGH), while representative only at the national and urban–rural level, are nonetheless designed to measure household income and expenditures more precisely.

The method consists of using the household survey as a random sample of the total population found in the census databases and choosing variables that are common to these two sources. The distribution of the variables selected 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 based on household survey data. The coefficients obtained through the model cannot be economically interpreted because 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.[10]

To construct the panel of poverty maps, we used microdata from the following sources: (1) 1990, 2000, and 2010 general population censuses; (2) the 2005 population count; and (3) the 1992, 2000, 2005, and 2010 ENIGH. To produce income measures at the municipal level, we followed Elbers et al. (2003) in pairing 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 of 2010 with the 2010 census. With the exception of the 1992 ENIGH and the 2000 population census, the remaining matches between the ENIGH 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 2438 municipalities in Mexico. However, hereafter, we consider the 2372 municipalities on which there are comparable income, poverty, and inequality data from the 1990–2010 panel of poverty maps. The 66 municipalities left out have been created over the last 20 years.

[9] Strictly speaking, population count data do not offer universal coverage because they consist, in fact, of surveys not censuses. However, the sample size is sufficiently large so that the data can be disaggregated to the municipal level, and the precision of estimates is extremely high.

[10] To construct poverty maps for a 20-year period, the analysis identified 15 variables common to the ENIGH and the census and population counts that can be used to generate around 35 indicators to construct the necessary income models. These variables include dwelling characteristics, sociodemographic 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 (for example, the Territorial Integration System, the National Population Council, and the Ministry of Social Development).

4.2. Crime indicators

Data on the total number of homicides in municipalities are derived from official figures made public by the SNSP. The SNSP compiles information through an extensive collaborative task force involving several state and federal enforcement agencies.[11] Data on total homicides in municipalities are available for the entire period under study, while monthly figures on drug- and non-drug-related crimes have been publicly released since late 2006.[12] In the analysis that follows, for each municipality, we have collapsed each of the crime variables available (total homicide rate, drug-, and non-drug-related homicide) on a yearly basis. In addition to SPNS data, official figures on total homicides by age-group and gender for 1990–2010 were collected from the National Institute of Statistics and Geography (INEGI).

4.3. Other sources of municipal data

We have also gathered data on aggregate public expenditures, literacy rates, and police expenditures in municipalities. The data on public expenditures were obtained from the State and Municipal System of Databases produced by INEGI. The data on literacy rates—our proxy for human capital—have also been obtained from publicly available data provided by INEGI, as are the data on public expenditures on police forces.

4.4. Summary statistics

As presented in Appendix Table A.1, the summary statistics for the 2372 municipalities we have followed over time show that mean real per capita income in Mexico was lower in 2010 than in 1990. This partly captures the effect of both the 1994–1995 Tequila Crisis, the dot-com bubble of 1999–2001, and the 2008–2009 global financial crisis. Alternative measures of social welfare such as the food poverty headcount ratio, the Gini coefficient, and literacy rates show marked improvements in 2010 (relative to 1990).[13] However, these positive trends are not as marked in magnitude with respect to the period from 2005 to 2010.

5. Estimation strategy

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

$$Y_{it} = \beta(Gini)_{it} + X_{it} \cdot \delta + \varepsilon_{it}, \qquad (1)$$

where $\varepsilon_{it} = \mu_i + \Omega_{it}$; i indexes a municipality in census or count year t; y is a local crime rate indicator such as total murders per 100,000 inhabitants; *Gini* is the municipality Gini coefficient; and the coefficient β indicates the estimated effect of income inequality on the 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:

$$\Delta Y_{it} = \beta(\Delta Gini)_{it} + \Delta X_{it} \cdot \delta + \Delta\varepsilon_{it}. \qquad (2)$$

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.

(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, and so on. However, higher crime rates may affect local inequality by diminishing the stock of physical capital and the 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. (2013) 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* percentile at each municipality. We then estimate to which *national* percentile of the income distribution each *local* income percentile belongs in the initial year. For example, a household in the top (bottom) percentile of a poor (rich) municipality might belong to one of the poorer (richer) percentiles in the national income distribution. Then, we allow the income of each local percentile to grow over time in line with the growth in 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 returns to skills and labor market institutions. In sum, this instrument allows 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 in municipalities. The construction of this instrument is similar to that of the shift-share instrumental variables that have been extensively used in applied labor economics studies to isolate shocks to the labor market (for example, see Bartik, 1991; Blanchard and Katz, 1992).

The instrumental variable approach will also help mitigate another potential source of bias. Because the local Gini coefficients have been estimated using the poverty mapping methodology (Elbers et al., 2003), they could be affected by measurement error, which may introduce an attenuation bias in the OLS estimates. Given that most of the time variation exhibited by our instrumental variable arises from national trends in the distribution of income, this helps mitigate the measurement error bias in our municipal income measures. To account for the fact that the instrument might be affected by measurement error, we pursue two approaches. First, all the specifications report bootstrapped standard errors clustered at the municipalities. Second, we deal with outliers by eliminating municipalities with extreme changes in crime or inequality in certain specifications, and we also report results using both the level and the logarithm of the crime rate.

[11] The Center for Investigation and National Security, the National Center for Information, Analysis, and Planning to Fight Crime within the Office of the Federal Attorney General, the Public Security Secretariat, the Secretary of National Defense, the Secretary of the Navy, and the Secretary of the Interior (Gobernacion) participate in this collaborative effort (Molzahn et al., 2013).

[12] To be considered a drug-related homicide by the SNPS, a homicide must meet at least two of the following criteria: (a) the victim was killed by high-caliber firearms; (b) victims with signs of torture or severe lesions; (e) victims found at the crime scene or in a vehicle; (d) victims whose bodies were taped, wrapped, or gagged; (e) the murder occurred in a prison and involved criminal organizations; and (f) one of several special circumstances occurred, including the victim was abducted prior to assassination (*levantón*), ambushed, or chased; the victim was an alleged member of a criminal organization; or a *narco-message* was left on or near the body (see Molzahn et al., 2013).

[13] 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) as the lack of sufficient income to acquire a basic food basket. The council presents national, urban, and rural income poverty estimates using INEGI data.

6. Results

Given the large dispersion in crime rates (see Appendix Fig. A.1), we estimate two alternative models: one using the number of crimes in levels and another using the logarithm of the number of crimes.[14] A naive OLS regression of (2) without addressing the reverse causality problem between income inequality and crime leads one to conclude that higher inequality deters crime (see Appendix Table A.2). In other words, increasing income inequality would be associated with lower crime rates in municipalities. According to the first column of panel a in Fig. A.2, a one-point increase in the Gini coefficient between 2007 and 2010 would be associated with a decrease of one drug-related murder per 100,000 inhabitants. The rest of the estimates in panels a and b confirm that, if the relationship is statistically significant, inequality is negatively correlated with crime, a counterintuitive result in comparison 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 because those households with less economic opportunities stay behind. In fact, there is empirical evidence that the increasing crime rates during the period significantly raised the geographical mobility of Mexican households. Ríos (2014) estimates that a total of 264,693 individuals migrated out of fear of organized crime activities in Mexico between 2005 and 2010. In addition, Rios presents anecdotal evidence indicating that a significant number of these migrants do not belong to the lower part of the income distribution. Thus, while total emigration from Mexico to the United States declined during this period, the number of investor visas issued to Mexican nationals rose by 300% from 2000 to 05 to 2005–2010.

Accordingly, a second mechanism may be driving the negative correlation between inequality and crime: rising crime rates may depress home values and thereby affect the wealth and incomes of homeowners and real estate owners who do not move out of crime-ridden areas. Indeed, Ríos (2014) 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. Appendix Table A.3 shows the results of the first-stage equation, that is, regressing the Gini coefficient using predicted inequality as the main explanatory variable. In Table A.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 the standard error is low. The F-statistics of excluded instruments are 97.5, 71.9, and almost 17.0 in 1990–2010, 2000–2010, and 2005–2010, respectively; all these surpass the conventional threshold for a strong instrument (see Stock and Yogo, 2005).

Panel a in Table A.3 shows that, for 1990–2010, 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 in 2005–2010, when 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, for which an increase in the Gini coefficient of about one point is associated with an increase of more than 10 deaths. These results are in sharp contrast with our OLS estimates, suggesting that income inequality had a significant effect on drug-related murders between 2005 and 2010. The estimates are quite large in magnitude relative to the actual changes in crime rates during this period: the number of drug-related deaths per 100,000 inhabitants rose by about 10 deaths between 2007 and 2010. In other words, changes in inequality within municipalities were significant in shaping the geography of drug-related crime rates during Mexico's drug war. Between 2005 and 2010, many municipalities (78% of the total) witnessed a narrowing in inequality, a pattern that was also observed at the national level. 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. Panel b in Table A.3 shows the estimated 2SLS coefficients using the logarithm of the number of crimes as the dependent variable, and they are largely consistent with those in Appendix Table A.4 given that the results are only significant for drug-related crimes. The magnitude of the effect, however, is smaller and implies that a one-point increase in the Gini coefficient raised the number of drug-related deaths per 100,000 inhabitants by 36%.

We do not find evidence that increasing inequality has had any effect on non-drug-related crimes between 2007 and 2010, which shows that the positive effects on the total homicide rate are driven by drug-related crimes. Thus, the increasing social tensions and pecuniary incentives for criminal activity associated with inequality did not seem to drive the geographical pattern of non-drug-related crimes after 2007. At the same time, the effect of inequality on the total homicide rate was significant, but substantially smaller if we consider the years 1990–2010. This 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 the DTOs. These models control for changes in poverty, whereby 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 in which rich households are becoming richer with respect to the rest of the households. These results are consistent with the economic and sociological theories of crime described in Section 2, since a widening of the gap between the rich and poor increases the potential rents of criminal activity. Because we are controlling for changes in poverty, these potential rents are associated with the higher incomes of the potential targets of criminal activities (the rich).

6.1. Robustness checks

To check the robustness of the main results presented above (Appendix Table A.4), we employ a variety of specifications. The first robustness exercise involves excluding outliers in our inequality measure, the Gini coefficient. To do so, we remove those municipalities in which 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. The results in appendix Table A.5, line 1 are similar in the order of magnitude and significance to the results presented in Table A.4.

We also estimate a specification using different poverty measures as control variables. In Mexico, the Technical Committee on Poverty Measurement has 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 A.4 are based on food poverty, the most restrictive monetary poverty indicator of the three given that it measures poverty as the household's lack of resources to maintain a minimum basic diet. Therefore, to show that our results are still robust, we replace our poverty measure by the two less restrictive ones.[15] As shown, the main results remain

[14] Fig. 2A in the Online Appendix presents the distribution in homicides rates for the years 1990, 2000, 2005 and 2010.

[15] Capacities poverty is defined as the lack of sufficient household resources to maintain expenditures on a minimum diet, education, and health care. Assets poverty expands the notion of capabilities poverty to include households that cannot afford clothing, housing, energy, and transportation expenditures.

unchanged in terms of magnitude and significance (see Table A.5, lines 2.1 and 2.2).

To account for the fact that the initial levels of inequality may drive the changes in crime and inequality we have observed, we estimate a model where we add as control variables the initial values of the Gini coefficient. Appendix Table A.5, line 3 shows that the results are still quite similar to the baseline results and even slightly larger in magnitude.[16]

Additionally, if we eliminate from the sample those municipalities with the largest increase in homicides, the results remain statistically significant, although slightly smaller in magnitude (Table A.5, line 4). Thus, our main findings are not driven by the municipalities that experienced the most dramatic increases in crimes. In a similar vein, we also exclude the municipalities located at the border between the United States and Mexico (Table A.5, line 9). Our findings are robust to this exercise.

Another robustness check was carried out by eliminating from the sample those municipalities in which inequality measures are less precise. Specifically, we ranked all municipalities using the standard errors associated with the Gini coefficients estimated with the poverty mapping methodology described in the data section and eliminated the top 5%. As Table A.5, line 5 shows, the coefficients still have the expected sign and are statistically significant, but they are slightly smaller in magnitude.

To demonstrate that our results are not driven by our selection of covariates (other than inequality), Table A.5, lines 6 and 7 present our result without controlling for poverty and without controlling for poverty, median income, and public expenditures, respectively. If we exclude our poverty measure, our results are similar to the results presented in Table A.4. When we exclude our measures of poverty, median income, and public expenditures altogether, our results are virtually the same as the results presented in Table A.4 (see Table A.5, line 7).

Finally, related to these robustness checks, we use the lagged first differences in our covariates as controls. The main purpose of this exercise is to use a variation that might be considered more exogenous (because it arises from differences in the previous half-decade) for covariates such as poverty that might suffer from a reverse causality type of concern. Our results are unaffected by this robustness check (see Table A.5, line 8).[17]

6.2. 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 of crime are greater in the former than in the latter (Glaeser and Sacerdote, 1999). 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; these shares also vary by type of crime. Guerrero (2011) points out that DTOs in Mexico have broadened the scope of their activities to other violent crimes (for example, kidnapping, extortion, and vehicle theft), which, in many cases, are associated with increases in the homicide rate. This, 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 because the change in the costs and benefits may have differed across areas as well.

Tables A.6 and A.7 present our results broken down by urban and rural municipalities.[18] We estimate two sets of models using either the levels or the logarithm of crimes. If we focus only on rural municipalities, even though the coefficients are larger in magnitude than the coefficients of urban areas, the statistical significance of our main findings disappears across specifications. The main effect is statistically significant at the 10% level for 1990–2010 if we use logarithms, but the coefficient is small. If we focus on urban municipalities, our results differ slightly depending on whether we use crime rates in levels or logs. In the case of the levels of crime rates, Table A.7 shows that higher levels of inequality raise both drug- and non-drug-related crimes throughout the period from 1990 to 2010. In particular, between 2007 and 2010, an increment of one point in the Gini coefficient increased drug-related homicides by about five deaths per 100,000 inhabitants. If we focus on the specification that uses the logarithms of crime rates, we find that a one-point increase in the Gini coefficient in urban municipalities raises drug-related crimes by 37%.

The fact that the effects are statistically significant only in urban municipalities is consistent with the effect of widening inequality and the associated rise in the expected benefits of criminal activity on crime rates because they are larger in areas where arrest probabilities are lower and where the pecuniary benefits are already at a higher level. The fact that the effects are weaker for non-drug-related crimes is also consistent with the baseline results.

6.3. Interaction with police spending

We are interested in exploring the existence of the heterogeneous effects of inequality across those municipalities that experienced different changes in the level of police spending. Table A.8 shows the estimates of a model that includes an interaction between the change in the Gini coefficient and the change in police spending. Unfortunately, municipal police spending is only available for 501 observations during this period; our sample is therefore significantly reduced. Under this specification, the parameter associated with the Gini coefficient is still positive, but no longer statistically significant. The parameter associated with the interaction between the Gini coefficient and spending on police, however, is negative and statistically significant. This suggests that the effect of inequality on crime was partially mitigated in municipalities that had a larger increase in police spending.

6.4. Results disaggregated by type of crimes

Table A.9 shows the results disaggregated by type of drug-related homicides. While homicides due to executions are driven by confrontations between members of DTOs, those due to aggressions are driven by both confrontations between DTOs and between DTOs and the armed forces and the general public.[19] According to panel a, Table A.9, most of the aggregate effects described above are driven by an increase in executions and not by an increase in aggression or confrontations. The latter is consistent with accounts such as the one presented by Dell (2015, 1740) which states that "over 85% of the total drug-related violence consists of drug traffickers killing each other, and the increases in violence are concentrated in municipalities that are plausibly the most valuable for drug trafficking organizations to control." Panel b, Table A.9 also shows that an increase in inequality produced a significantly larger increase in executions and confrontations than aggressions.

[16] To control for possible omitted characteristics that vary by state and year, we also include state-year fixed effects. Table A.5, line 10 shows that our findings are robust to the inclusion of state-year fixed effect controls.

[17] Table I.B in the online Appendix presents the same robustness checks as in Table A.5, but the homicide rates in levels are used as a dependent variable instead of the logarithm of the homicide rates.

[18] Urban municipalities are defined in this paper according to the National Population Council's definition of urban areas. A municipality with more than 15,000 inhabitants is considered urban, and a municipality with fewer than 15,000 inhabitants is considered a rural or semi-urban area.

[19] More specifically, according to the SNPS, homicides due to confrontations and executions do not involve casualties of members of the armed forces. Data on homicides related to aggressions, on the other hand, account for confrontations between DTOs and the armed forces (see Robles et al., 2013).

Given that the victims of homicides due to drug-related executions are likely to belong to a DTO, a breakdown of crime rates by the socioeconomic characteristics of drug-related crimes could be good proxy variables for the characteristics of the perpetrators.

6.5. Results by demographic characteristics

Table A.10 shows the results using homicide rates disaggregated by the age of the victim, which, according to the analysis above, would be a good proxy variable for the age of the DTO members. As expected, Table A.10 shows that the estimates are larger for prime-age individuals; the effects peak at ages 30 to 44. This is consistent with the idea that inequality increases crime rates by raising the pecuniary incentives to criminal activities because an increase in inequality increases the income gap proportionally more between those at the top and those with reasonable labor market opportunities than between those at the top and those at an even lower level of the age-earnings profile.[20] Accordingly, the decrease in the cost of criminal activities associated with the proliferation of DTOs is more likely to affect prime-age individuals than individuals 15 years old or younger because the latter tend to discount more heavily the probability of being caught and are thereby less responsive to a decrease in this parameter (Becker, 1995). Theories arguing that inequality would increase crime by raising social tensions or deprivation would predict that the rate of offense should increase more among those with poorer labor market prospects.[21]

7. Concluding remarks

The effect of inequality on crime has been empirically addressed by many scholars, but with mixed results and mostly in developed economies. This paper estimates the effect of income inequality on crime in a unique context: Mexico's drug war. During this period, DTOs multiplied and expanded geographically across the country, facilitating the incorporation of individuals into criminal activities. We exploit a rich dataset containing within-country variations in inequality and crime rates for the more than 2000 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 from 2007 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, if we differentiate between different types of crimes, we find that the effect is even larger for drug-related crimes, that is, 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 (or to an increase of 36% according to an alternative specification). The results are large if they are compared with the overall rise 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 the 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 if we consider the entire period between 1990 and 2010.

In the case presented in this paper, we argue that the increase in rents to be extracted through crime is accompanied by an increase in the employment opportunities in the illegal sector through the proliferation of DTOs, combined with a decrease in legal job opportunities and a reduction in the probability of being caught, because of the resource constraints faced by the law enforcement system. These effects, combined, make criminal activity a rational decision for a larger group of people. Our results are consistent with this hypothesis. These more rational elements can then be reinforced by social disorder and loss of social capital, which feeds back into the negative dynamics. Further work could focus precisely on disentangling the actual magnitudes of these effects. This paper's main contribution, however, is to isolate and quantify the magnitude of the causal direction of the interaction between inequality and crime.

[20] Consistent with this result, Tables A.11 and A.12 show that this effect is larger among men between 15 and 45 years of age than among women in this same age-group.

[21] In Tables A.2–A.12, we focus on presenting the coefficient associated with inequality. However, unless otherwise noted, all the specifications include other covariates such as median income, poverty, rural population, public expenditures, literate population, and year fixed effects. Tables 1C–23C in the Online Appendix reproduce the results presented in Tables A.2–A.12, but present the coefficients for the other covariates used to identify the causal effect of inequality on crime rates in Mexico (1990–2010).

Appendix A

Table A.1
Descriptive statistics.

	Mean	Std. dev.	Mean	Std. dev.
	1990		2000	
Real income[a]	18,363.31	8890.44	16,657.37	9838.59
Gini coefficient[a]	0.43	0.06	0.38	0.06
Food poverty headcount[a]	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
Rate of total homicides[b]	15.75	35.85	8.90	20.69
Total population[c]	33,913.10	100,515.40	40,395.87	120,041.60
No. of observations	2372		2372	
	2005		2005	
Real income[a]	17,971.46	9538.98	17,614.54	9361.99
Gini coefficient[a]	0.38	0.05	0.34	0.04
Food poverty headcount[a]	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	2324.52	1757.12	3037.27	2267.26
Literacy rate	0.83	0.11	0.86	0.10
Rate of total homicides[b]	7.86	22.17	21.40	79.49
Rate of drug-related homicides[b, d]	2.30	17.85	14.60	77.19
Rate of non-drug-related homicides[b, d]	5.56	12.84	6.79	17.17
Total population[c]	42,700.54	127,528.60	45,666.65	130,964.00
No. of observations	2372		2372	

[a]Calculations using the ENIGH, population census and population counts.
[b]Per 100,000 individuals.
[c]Consejo Nacional de Población. All monetary figures are in per capita and real terms as August of 2010.
[d]Homicides rates for drug and non-drug-related activities are representative of 2007, not 2005.

Table A.2
The impact of inequality on homicide rates for Mexican municipalities (1990–2010).

	Homicide rate — drug-related crimes	Homicide rate — non-drug-related crimes	Homicide rate		
	2007–2010	2007–2010	1990–2010	2000–2010	2007–2010
a. OLS estimates (homicide rates)					
ΔGini	−104.029*	−31.412***	−14.296	−21.524	−96.315*
	(59.913)	(9.471)	(13.947)	(24.434)	(59.853)
Number of obs.	1872	1872	5991	3839	1872
b. OLS estimates (log of homicide rates)					
ΔGini	0.198	−0.009	0.022	−0.084	−0.793**
	(0.440)	(.341)	(0.152)	(0.193)	(0.392)
Number of obs.	1872	1872	5991	3839	1872

Dependent variable: panel a: difference in homicide rates. Panel b: logarithm of the difference in homicide rates.
All specifications include the following additional controls: ΔLog Median Income, ΔPoverty, Δ% Rural Population, ΔLog Public Expenditures, ΔLog Literate Population, and Year Fixed Effects.
Bootstrapped Std. errors clustered at the municipal level (2500 replications) are presented within parentheses.
Monetary measures are expressed in real terms as August of 2010.
All regressions are weighted by municipal population size.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.3
The impact of predicted inequality on observed inequality in municipalities, 1990–2010.

First-stage regressions			
	Gini	Gini	Gini
	1990–2010	2000–2010	2005–2010
ΔPredicted Gini —- instrument	1.360***	0.910***	0.864***
	(0.091)	(0.073)	(0.293)
Number of obs.	5991	3839	1872

Dependent variable: difference in Gini.
All specifications include the following additional controls: ΔLog Median Income, ΔPoverty, Δ% Rural Population, ΔLog Public Expenditures, ΔLog Literate Population, and Year Fixed Effects.
Bootstrapped std. errors clustered at the municipal level (2500 replications) are presented within parentheses.
Monetary measures are expressed in real terms as August of 2010.
All regressions are weighted by municipal population size.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.4
The impact of Inequality on homicide rates for Mexican municipalities (1990–2010).

	Homicide rate — drug-related crimes	Homicide rate — non-drug-related crimes	Homicide rate		
	2007–2010	2007–2010	1990–2010	2000–2010	2007–2010
a. 2SLS estimates (homicide rates)					
ΔGini	1,173.800*	27.217***	85.025***	5.406	1201.017*
	(645.043)	(96.883)	(31.370)	(30.399)	(653.912)
Number of obs.	1872	1872	5991	3839	1872
b. 2SLS estimates (log of homicide rates)					
ΔGini	31.416**	6.004	1.367***	1.883***	24.106**
	(13.216)	(4.612)	(0.513)	(0.726)	(10.365)
Number of obs.	1872	1872	5991	3839	1872

Dependent variable: panel a: difference in homicide rates. Panel b: logarithm of the difference in homicide rates.
All specifications include the following additional controls: ΔLog Median Income, ΔPoverty, Δ% Rural Population, ΔLog Public Expenditures, ΔLog Literate Population, and Year Fixed Effects.
Bootstrapped std. errors clustered at the municipal level (2500 replications) are presented within parentheses.
Monetary measures are expressed in real terms as August of 2010.
All regressions are weighted by municipal population size.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.5
Alternative specifications: the impact of inequality on homicide rates for Mexican municipalities (1990–2010).

	Drug related homicides	Non-drug related homicides	Homicide rate		
	2007–2010	2007–2010	1990–2010	2000–2010	2007–2010
1. Trimming for outliers in inequality (high levels of inequality)	30.029**	4.006	1.481**	1.926*	22.422*
	(15.934)	(5.006)	(0.620)	(0.769)	(12.004)
2. Controlling by alternative poverty measures:					
2.1. Capacities poverty	31.854**	6.261	1.337***	2.461***	24.546**
	(13.387)	(4.746)	(0.521)	(0.805)	(10.538)
2.2. Assets poverty	42.928*	9.212	1.402**	1.936***	33.107*
	(24.164)	(7.494)	(0.563)	(0.589)	(18.917)
3. Including initial levels in inequality	41.953***	9.949*	0.433	2.198***	33.608**
	(16.469)	(5.325)	(0.648)	(0.663)	(13.169)
4. Trimming for outliers in crime	19.048***	0.847	0.911**	0.978	14.770**
	(7.251)	(3.000)	(0.457)	(0.651)	(5.901)
5. Trimming for outliers in inequality (high std. errors — poverty maps)	18.372***	2.534	1.246***	1.803**	15.016***
	(4.535)	(2.688)	(0.573)	(0.754)	(3.907)
6. Not controlling for poverty	37.461**	7.558	1.448**	2.140**	28.748**
	(17.326)	(5.789)	(0.526)	(0.771)	(13.566)
7. Not controlling for poverty, expenditures, and income	32.014**	7.169*	1.467***	1.799***	24.374***
	(11.005)	(4.335)	(0.455)	(0.644)	(8.647)
8. Using lag first differences as covariates	28.342**	7.676*		1.335**	22.602**
	(11.349)	(4.803)		(0.742)	(9.166)
9. Exclude municipalities located at the border between the U.S. and Mexico	27.611**	4.684	1.298**	1.689**	21.373**
	(11.540)	(4.172)	(0.515)	(0.724)	(9.241)
10. State-year fixed effects	35.295**	6.463	0.035	1.454***	25.020*
	(20.518)	(6.935)	(0.794)	(0.533)	(15.123)

Dependent Variable: Logarithm of the difference in homicide rates.
Unless otherwise noted all specifications include the following additional controls: ΔLog Median Income, ΔPoverty, Δ% Rural Population, ΔLog Public Expenditures, ΔLog Literate Population, and Year Fixed Effects.
Robust Std. Errors (clustered at the municipal level) are presented within parentheses.
Monetary measures are expressed in real terms as August of 2010.
All regressions are weighted by municipal population size.

Table A.6
The impact of inequality on homicide rates for Mexican municipalities (1990–2010).

Rural municipalities					
	Homicide rate — drug-related crimes	Homicide rate — non-drug-related crimes	Homicide rate		
	2007–2010	2007–2010	1990–2010	2000–2010	2007–2010
a. 2SLS estimates (homicide rates)					
ΔGini	3095.047	−153.108	89.061**	28.120	2941.939
	(8238.584)	(486.924)	(47.447)	(66.090)	(7919.156)
Number of obs.	973	973	3219	2018	973
b. 2SLS estimates (log of homicide rates)					
ΔGini	15.709	−0.682	1.030**	−0.732	12.763
	(42.177)	(9.562)	(0.515)	(0.750)	(36.031)
Number of obs.	973	973	3219	2018	973

Dependent variable: panel a: difference in homicide rates. Panel b: logarithm of the difference in homicide rates.
All specifications include the following additional controls: ΔLog Median Income, ΔPoverty, Δ% Rural Population, ΔLog Public Expenditures, ΔLog Literate Population, and Year Fixed Effects.
Bootstrapped std. errors clustered at the municipal level (2500 replications) are presented within parentheses.
Monetary measures are expressed in real terms as August of 2010.
All regressions are weighted by municipal population size.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.7
The impact of Inequality on Homicide Rates for Mexican Municipalities (1990–2010).

Urban municipalities	Homicide rate — drug-related crimes	Homicide rate — non-drug-related crimes	Homicide rate		
	2007–2010	2007–2010	1990–2010	2000–2010	2007–2010
a. 2SLS estimates (homicide rates)					
ΔGini	532.570**	54.536	77.105***	44.566**	587.107**
	(214.028)	(71.856)	(29.630)	(19.203)	(234.992)
Number of obs.	906	906	2794	1835	906
b. 2SLS estimates (log of homicide rates)					
ΔGini	32.150***	6.900*	1.738**	2.502***	24.874***
	(9.031)	(4.233)	(0.936)	(0.890)	(7.159)
Number of obs.	906	906	2794	1835	906

Dependent variable: panel a: difference in homicide rates. Panel b: logarithm of the difference in homicide rates.
All specifications include the following additional controls: ΔLog Median Income, ΔPoverty, Δ% Rural Population, ΔLog Public Expenditures, ΔLog Literate Population, and Year Fixed Effects.
Bootstrapped std. errors clustered at the municipal level (2500 replications) are presented within parentheses.
Monetary measures are expressed in real terms as August of 2010.
All regressions are weighted by municipal population size.
***p < 0.01, **p < 0.05, *p < 0.1.

Table A.8
The impact of inequality on homicide rates for Mexican municipalities (1990–2010). Estimates including an interaction term between inequality and police spending.

	Homicide rate — drug-related crimes	Homicide rate — non-drug-related crimes	Homicide rate
	2007–2010	2007–2010	2007–2010
a. 2SLS estimates (homicide rates)			
ΔGini	1922.667	−93.131	1829.536
	(2604.748)	(533.061)	(2510.985)
ΔPolice spending	62.374**	−1.784	60.590
	(30.929)	(10.704)	(53.341)
ΔGini * ΔPolice spending	−162.434	4.891	−157.542
	(142.140)	(27.490)	(136.995)
Number of obs.	501	501	501
b. 2SLS estimates (log of homicide rates)			
ΔGini	59.085	28.397	52.959
	(75.485)	(39.759)	(65.789)
ΔPolice spending	1.685	0.709	1.591
	(1.589)	(0.814)	(1.373)
ΔGini * ΔPolice spending	−4.325	−1.840	−4.090
	(4.072)	(2.085)	(3.518)
Number of obs.	501	501	501

Dependent variable: panel a: difference in homicide rates. Panel b: logarithm of the difference in homicide rates.
All specifications include the following additional controls: ΔLog Median Income, ΔPoverty, Δ% Rural Population, ΔLog Public Expenditures, ΔLog Literate Population, and Year Fixed Effects.
Bootstrapped STD. Errors clustered at the municipal level (2500 replications) are presented within parentheses.
Monetary measures are expressed in real terms as August of 2010.
All regressions are weighted by municipal population size.
***p < 0.01, **p < 0.05, *p < 0.1.

Table A.9
The impact of inequality on homicide rates for Mexican municipalities (2007–2010). Different types of drug-related homicides.

	Rate of homicides due to aggressions	Rate of homicides due to executions	Homicide rate of homicides due to confrontations
	2007–2010	2007–2010	2007–2010
a. 2SLS estimates (homicide rates)			
ΔGini	5.410	724.257**	444.133
	(44.559)	(373.873)	(332.154)
Number of obs.	1872	1872	1872
b. 2SLS estimates (log of homicide rates)			
ΔGini	4.850	28.356**	12.591**
	(3.047)	(12.084)	(45.522)
Number of obs.	1872	1872	1872

Dependent variable: panel a: difference in homicide rates. Panel b: logarithm of the difference in homicide rates.
All specifications include the following additional controls: ΔLog Median Income, ΔPoverty, Δ% Rural Population, ΔLog Public Expenditures, ΔLog Literate Population, and Year Fixed Effects.
Bootstrapped std. errors clustered at the municipal level (2500 replications) are presented within parentheses.
Monetary measures are expressed in real terms as August of 2010.
All regressions are weighted by municipal population size.
***p < 0.01, **p < 0.05, *p < 0.1.

Table A.10
Impact of inequality on homicide rates in municipalities, by age-group, 2007–2010.

	Homicide rate 0–14 years of age	Homicide rate 15–29 years of age	Homicide rate 30–44 years of age	Homicide rate 45–59 years of age	Homicide rate 60+ years of age
	2007–2010	2007–2010	2007–2010	2007–2010	2007–2010
a. 2SLS estimates (homicide rates)					
ΔGini	9.286	348.478*	428.188*	−47.823	−16.332
	(23.302)	(205.519)	(250.419)	(78.782)	(42.049)
Number of obs.	1872	1872	1872	1872	1872
b. 2SLS estimates (log of homicide rates)					
ΔGini	2.433	18.864**	19.405**	9.727*	2.139
	(1.751)	(8.413)	(8.553)	(5.045)	(2.752)
Number of obs.	1872	1872	1872	1872	1872

Dependent variable: panel a: difference in homicide rates. Panel b: logarithm of the difference in homicide rates.
All specifications include the following additional controls: ΔLog Median Income, ΔPoverty, Δ% Rural Population, ΔLog Public Expenditures, ΔLog Literate Population, and Year Fixed Effects.
Bootstrapped std. errors clustered at the municipal level (2500 replications) are presented within parentheses.
Monetary measures are expressed in real terms as August of 2010.
All regressions are weighted by municipal population size.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.11
The impact of Inequality on Homicide Rates for Mexican Municipalities (1990–2010).

Females 15–45 years old			
	Rate of homicides	Rate of homicides	Rate of homicides
	1990–2010	2000–2010	2007–2010
a. 2SLS estimates (homicide rates)			
ΔGini	−2.934	2.396	47.000
	(4.568)	(8.838)	(30.684)
Number of obs.	5991	3839	1872
b. 2SLS estimates (log of homicide rates)			
ΔGini	0.101	0.886**	8.793**
	(0.228)	(0.382)	(4.044)
Number of obs.	5991	3839	1872

Dependent variable: panel a: DIFFERENCE in homicide rates. Panel b: Logarithm of the difference in homicide rates.
All specifications include the following additional controls: ΔLog Median Income, ΔPoverty, Δ% Rural Population, ΔLog Public Expenditures, ΔLog Literate Population, and Year Fixed Effects.
Bootstrapped std. errors clustered at the municipal level (2500 replications) are presented within parentheses.
Monetary measures are expressed in real terms as August of 2010.
All regressions are weighted by municipal population size.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.12
The impact of Inequality On Homicide Rates for Mexican municipalities (1990–2010).

Males 15–45 years old			
	Rate of homicides	Rate of homicides	Rate of homicides
	1990–2010	2000–2010	2007–2010
a. 2SLS estimates (homicide rates)			
ΔGini	29.562	−4.477	721.626*
	(23.033)	(27.233)	(416.897)
Number of obs.	5991	3839	1872
b. 2SLS estimates (log of homicide rates)			
ΔGini	0.592	2.128***	19.336**
	(0.508)	(0.724)	(8.867)
Number of obs.	5991	3839	1872

Dependent variable: panel a: difference in homicide rates. Panel b: logarithm of the difference in homicide rates.
All specifications include the following additional controls: ΔLog Median Income, ΔPoverty, Δ% Rural Population, ΔLog Public Expenditures, ΔLog Literate Population, and Year Fixed Effects.
Bootstrapped std. errors clustered at the municipal level (2500 replications) are presented within parentheses.
Monetary measures are expressed in real terms as August of 2010.
All regressions are weighted by municipal population size.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

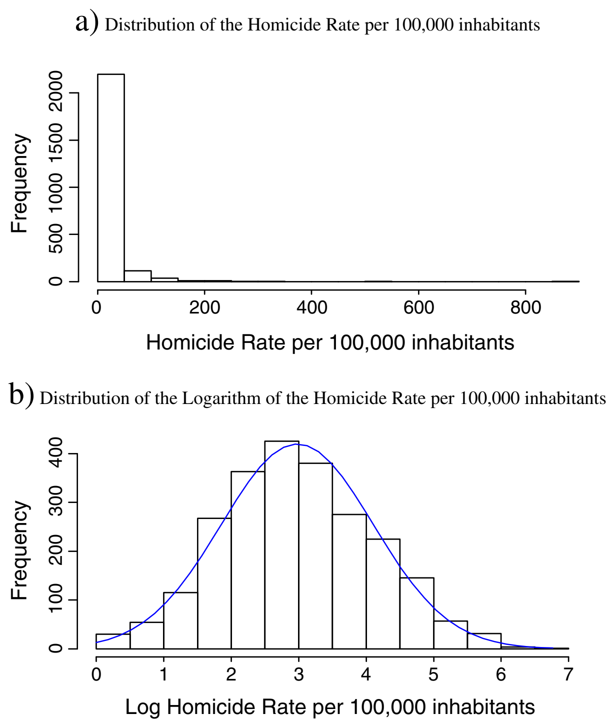

Fig. A.1. Distribution of homicide rates in 2010. a. Distribution of the homicide rate per 100,000 inhabitants. b. Distribution of the logarithm of the homicide rate per 100,000 inhabitants.

Appendix B. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jdeveco.2015.12.004.

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