IDB WORKING PAPER SERIES No. IDB-WP-471

On the Distributive Costs of Drug-Related Homicides

Nicolás Ajzenman
Sebastián Galiani
Enrique Seira

January 2014

Inter-American Development Bank
Department of Research and Chief Economist

On the Distributive Costs of Drug-Related Homicides

Nicolás Ajzenman*
Sebastián Galiani**
Enrique Seira***

* Kennedy School of Government, Harvard University
** University of Maryland
*** Instituto Tecnológico Autónomo de México

Inter-American Development Bank
2014

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

Ajzenman, Nicolás.
On the distributive costs of drug-related homicides / Nicolás Ajzenman, Sebastián Galiani, Enrique Seira.
p. cm. — (IDB Working Paper Series ; 471)
Includes bibliographic references.
1. Crime—Mexico—Economic aspects. 2. Homicide—Mexico—Economic aspects. 3. Drug traffic—Mexico —Economic aspects. 4. Housing—Prices. I. Galiani, Sebastián. II. Seira, Enrique. III. Inter-American Development Bank. Department of Research and Chief Economist. IV. Title. V. Series.
IDB-WP-471

http://www.iadb.org

Abstract[*]

There are few reliable estimates of the effects of violence on economic outcomes. This study exploits the manifold increase in homicides in 2008-2011 in Mexico resulting from its war on organized drug traffickers to estimate the effect of drug-related homicides on housing prices. Using an unusually rich dataset that provides national coverage on housing prices and homicides and exploits within-municipality variation, the study finds that the burden of violence affects only the poor. An increase in homicides equivalent to one standard deviation leads to a 3 percent decrease in low-income housing prices. Moreover, the effect on housing prices of long-term increases in crime is 40 percent larger.

JEL: K4, I3
Keywords: Drug-related homicides, Poverty, Costs of crime

[*] This paper was undertaken as part of the project "The Costs of Crime in Latin America and the Caribbean." We are grateful to the Inter-American Development Bank (IDB) for the financial support received for this project. We also wish to thank the IDB seminar participants for their comments.

1. Introduction

Drug production and trafficking are a major problem in many countries. These activities are often associated with violence, insecurity, and corruption in the police force and in the legal system. In some countries, the sheer number of drug-related killings that take place may have a negative impact on economic outcomes.

In Mexico, there have been more than 50,000 drug-related homicides (DRHs) since 2006, when President Calderón took office and declared a war on drugs.[1] Compared to the number of deaths associated with other recent conflicts, such as the campaigns waged by the Irish Republican Army (3,500)[2] or ETA (1,000) in Spain,[3] the number of homicides in Mexico is more than an order of magnitude higher. As a result of this violence, five Mexican cities are among the 10 most violent cities in the world,[4] and Mexican citizens consider drug-related violence to be their most important concern.[5] Many analysts and prominent policymakers have estimated that this situation translates into a reduction in GDP of as much as 1 to 2 percentage points.[6] Although these estimates are more in the nature of guesses, rather than the result of any rigorous attempt to measure the economic causal effect of drug-related violence, they nonetheless provide some idea of the general perception of the scale of the potential damage to the economy generated by this type of violence.

This paper estimates the effect of violence on housing prices, using a unique dataset of housing prices compiled from information on all houses and apartments appraised between 2008 and 2011 in connection with mortgage applications. Housing prices are not only important in and of themselves, but they also reflect the amenities—or the dis-amenities—of living in certain locations. To measure the causal impact of homicides on housing prices, we take advantage of a rich dataset containing more than 1.3 million appraisals. These appraisals are distributed among more than a thousand of the country's municipalities (out of a total of 2,445) and take various

[1] As compared to the 8,901 cases registered in 2000-2006 (Ríos, 2012).
[2] Besley and Mueller (2011).
[3] Estimates prepared by Victims of Terrorism Association [http://www.avt.org/].
[4] Measured as homicides per 100,000 inhabitants, the rates for these five Mexican cities are: Ciudad Juárez: 148, Acapulco: 128, Torreón: 88, Chihuahua: 83, and Durango: 80. According to Consejo Ciudadano para la Seguridad Pública y la Justicia Penal, A.C., this puts these cities in the top 10 worldwide in 2011.
[5] Consulta Mitofsky, Monitor Mensual (survey), June 2011.
[6] The Governor of the Central Bank, Agustín Carstens, said it is "the most important factor inhibiting growth and investment." *Proceso Magazine*, April 6, 2011. See also the BBVA estimate issued in late 2010 and the statement made by the Minister of the Treasury, Ernesto Cordero, who estimated the reduction in GDP caused by the violence at 1.2 percent. Reuters, September 1, 2010.

dwelling characteristics into account. For statistics on homicides, we use a national dataset of deaths (focusing specifically on murders) collected by the Mexican Federal Secretariat of Health.

The sharp increase in DRHs allows us to identify the causal effects that are of interest to us here. We contend that the nature of local DRHs is unrelated to local economic conditions, since they are mainly associated with retaliation killings, battles among drug organizations, and clashes with the Army. We show some evidence of this in the paper.

Our findings indicate that increases in DRHs have a negative effect on housing prices, but only in the case of low-quality housing. In other words, this negative impact on housing prices is borne entirely by the poorer segments of the population. Using a hedonic price equation while conditioning on municipality fixed effects, period effects, secular trends by type of housing, and specific state trends, as well as controlling for a large set of dwelling characteristics, we estimate that a one standard deviation increase in homicides lowers the price of poor-quality houses by more than 3 percent. Given that many municipalities registered DRH increases much greater than 100 percent and that housing wealth is typically the largest source of wealth for Mexican families—and especially for low-income households—the economic costs of this type of violence could be substantial. Furthermore, we find that when the increase in violence is a long-term phenomenon, the negative effects on housing prices for the poor are about 40 percent larger. Our results are robust across different sources of data on homicides.

Our paper is closely related to that of Besley and Mueller (2012), who look at the effect of violence in Northern Ireland on housing prices. They exploit the spatial and temporal variation in violence and model the transition from violence to peace with a Markov switching model. They find that peace leads to an increase in housing prices of between 1.3 and 3.5 percent, with the effect being stronger in the regions where the violence was greatest.

The findings described in this paper are in line with those of Di Tella et al. (2010), who also find that violence places a heavy burden on the poor in another environment and type of conflict. They exploit the sharp increase in crime in the second half of the 1990s, specifically in 2001 in Buenos Aires, Argentina. Their main research question is whether the rich or the poor have been the main victims of this rise in crime. In the case of home robberies, they find that the poor are the primary victims of the increase in such crimes, but the channel for this effect is the fact that the rich, unlike the poor, are able to protect their homes by hiring security services and/or installing security devices.

The remainder of this paper is structured as follows. Section 2 describes the political context in which Mexico has experienced this DRH increase. The datasets employed for crime and housing variables are presented in Section 3. Section 4 discusses the related literature. Section 5 covers the identification strategy that was used and the main results. Section 6 presents a battery of robustness checks for the results discussed in the preceding section. Section 7 explores what happens when violence is persistent, and Section 8 concludes.

2. Recent Increases in Drug-Related Homicides in Mexico

Drug-related homicides in Mexico started to rise in 2006. These homicides rose sharply starting in 2008, with the cumulative total climbing to almost 50,000 cases by the end of 2011; by contrast, during the preceding presidential term (2000-2006), the number of DRHs was below 10,000 (Ríos, 2012). Some analysts believe that this sharp upswing is attributable to President Calderón's frontal attack on drug-trafficking organizations (DTOs), which he launched almost as soon as he took office in December 2006.[7] The hypothesis is that the killings and the apprehension of DTO leaders fragmented these organizations, which split into many different units and began to fight each other to gain control of their areas of operation (Ríos, 2012; Guerrero, 2011). Other analysts claim that when the Institutional Revolutionary Party lost the presidency after holding sway for almost 70 years, there was no longer a single political power to keep the DTOs in check and to strike deals with them (Astrogyan and Shirk, 2011; Bailey and Godson, 2000; Snyder and Durán-Martínez, 2009). In addition, some authors contend that the successful fight against drug-trafficking organizations in Colombia displaced operations to Mexico and led to increased violence there as DTOs strove to gain the upper hand in their areas of operation (Castillo et al., 2012).

All of these hypotheses are based on reasonable arguments, although it is difficult to disentangle their effects. In any case, it is well documented that the increase in violence coincided with the start of the Army's operations throughout the country (Escalante, 2011). Dell (2012), exploiting a regression discontinuity design applied to close elections, shows that municipalities in which the mayor belonged to the same party as the president witnessed more DRHs just after the crackdowns in Mexico began. Her empirical evidence suggests that the

[7] On December 11, 2006, the President sent the Army to Michoacán to fight drug dealers in what was called the Joint Michoacán Operation (Operativo Conjunto Michoacán).

violence reflects rival traffickers' attempts to usurp territories after a crackdown has weakened the position of the incumbent DTO.[8] Dell's (2012) results support qualitative and descriptive studies which advance the argument that the Mexican government's anti-drug policies have been the primary cause of the sharp increase in violence seen in recent years.

Dell (2012) also states that the number of major DTOs increased from 6 in 2007 to 16 by 2011, with groups splitting into factions as a result of leadership disputes. The fragmentation of these organizations and the ensuing struggle for preeminence and territory are, according to this view, the most likely causes of the increase in violence. According to Molzahn, Ríos, and Shirk (2012), of the 50,000 DRHs in 2006-2011, about 35,000 were due to conflicts among DTOs. Castillo et al. (2012) draw attention to the fact that the violence has been concentrated in municipalities where two or more cartels operate, with the presence of each additional cartel in a particular location bringing about an increase in the homicide rate of about 100 percent.

A second probable exogenous shock to the crime rate is related to Colombia's crackdown on DTOs. Castillo et al. (2012) exploit drug seizures in Colombia to account for the DRH rate in Mexico, arguing that these seizures could account for 17 percent of the increase in DRHs in Mexico.

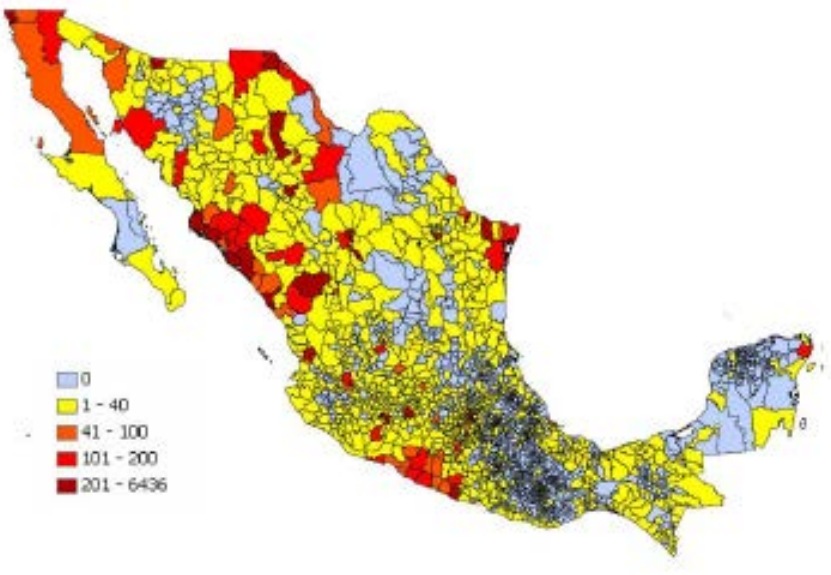
Regardless of whether the spike in DRHs is attributable to political factors or to the consequences of an exogenous shock to the crime rate generated by Colombia's successful war on drugs, it is unlikely that it resulted from changes in the demand side of the drug market, since most drug demand is external,[9] inasmuch as Mexico is the main provider of illicit drugs to the United States and demand there has not undergone any major or sudden change during the period in question (United Nations Office on Drugs and Crime, 2011).

One interesting characteristic of the situation in Mexico is that the violence tends to be geographically concentrated (see Figure 1). This may have to do with the localized nature of drug production. Indeed, Dell (2012) reports that illicit drugs are cultivated in 14 percent of the country's municipalities. It may also have something to do with proximity to transportation routes to the U.S. border and along the Pacific Coast (Castillo et al., 2012).

[8] According to Dell (2012): "Over 85 percent of the drug violence consisted of people involved in the drug trade killing each other" either as a way of extracting revenge or as a way of expanding their territories. She also notes that the killings are especially frequent after one side is weakened by government intervention.

[9] Whereas 14 percent of Americans have used illicit drugs during the past year (U.S. National Survey on Drug Use and Health), only 1.4 percent of Mexicans have done so (Encuesta Nacional de Adicciones, 2008).

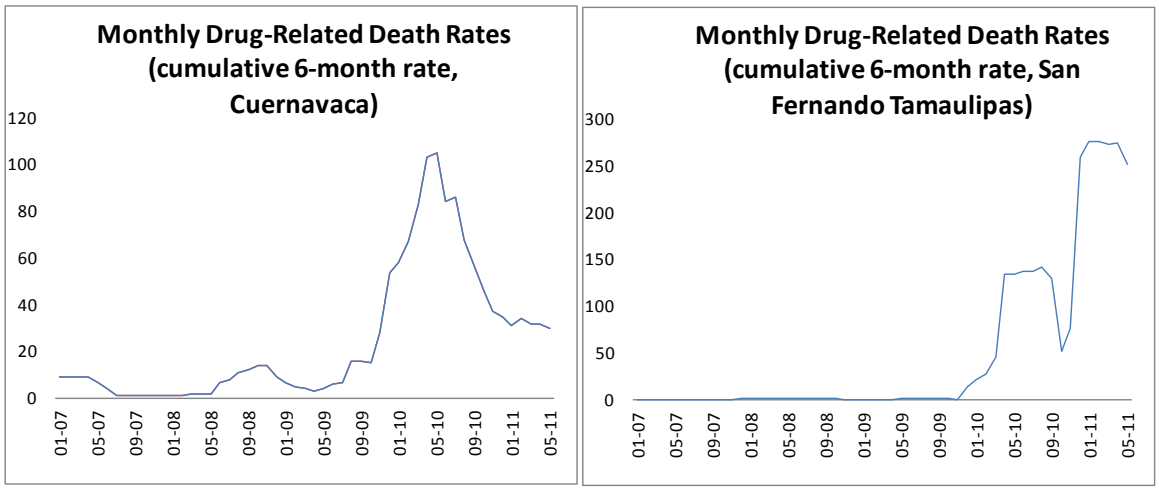
Figure 1. Total Drug-Related Homicides, by Municipality, 2007-2010



Source: Díaz-Cayeros et al. (2011).

Nevertheless, at the municipality level, we find that the increase in violence was sudden and discontinuous and that it occurred in different municipalities at different times, regardless of the economic or social characteristics of any particular municipality. Figure 2 shows examples of the spikes seen in DRHs in two of the most affected municipalities, but these patterns are present in dozens of others as well.

Figure 2. Dynamics of Drug-Related Homicides



Source: National Health Information System (SINAIS), Mexico.

Given that property crime has not been found to be strongly correlated with economic variables such as unemployment,[10] and in view of the patterns that we have described, it comes as no surprise that DRHs are not correlated with employment either. This finding will be discussed in Section 5.

Finally, another important fact to note here about DRHs is that they are generally more common in poor sectors of the population. First, drug dealers are usually recruited from low-income segments of the population. *Proceso*, a popular news magazine, calls the poor the "stockfeed of the illicit drug industry."[11] In their study on a gang of drug dealers, Levitt and Venkatesh (2000) find that such gangs hire low-income individuals and that almost all of them earn very low wages. This is very important, since we are interested in the distributional impact of crime. If the drug related crime is poverty-biased, and especially if it occurs in poor areas, then we can expect it to have different impacts on poor and non-poor populations.

3. Data and Descriptive Statistics

One of the strengths of this paper is the quality of the data on both of the main factors involved: homicides and housing prices. To measure homicides, we use two data sources: one is the data on DRHs reported by the Office of the President, compiled from the registries of several government ministries in Mexico. The other is the data collected from hospitalization records, which register all homicide deaths (whether drug-related or not). For housing price data, we use a house appraisal database that covers 25 house appraisal characteristics and 1,370,676 valuations. The period for which pricing data are available runs from January 2008 through December 2011, and our final dataset therefore covers exactly that period.

3.1 Crime Data

Death certificates issued by civil servants and doctors are our main source of data on homicides. This dataset contains variables that identify the cause of death, the date of death, and the place where it occurred. This information is centralized by the National Health Information System (*Sistema Nacional de Información en Salud*—SINAIS). The SINAIS database contains a registry

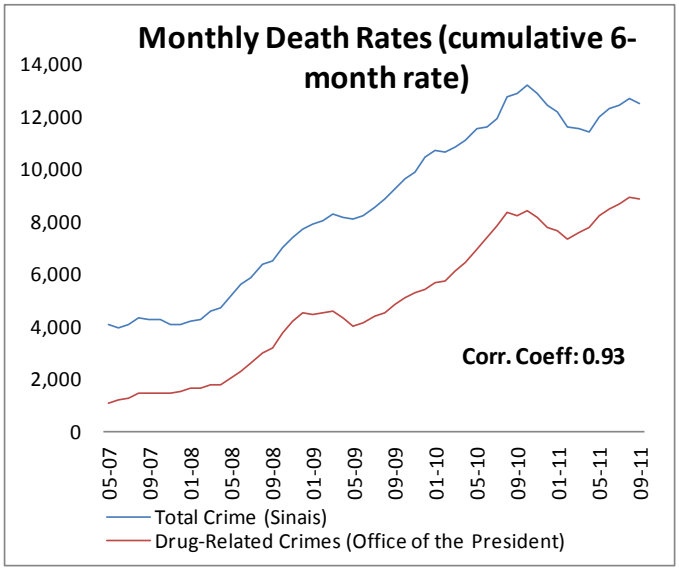
[10] A typical estimate would be that a one-percentage-point increase in the unemployment rate is associated with a 1 percent increase in property crime (Levitt 2004).
[11] "Pobres, la reserva del narco," in *Revista Proceso*, 8 March 2011 [http://www.proceso.com.mx/?p=277851].

of deaths in Mexico but does not provide a clear indication of whether or not homicide deaths were related to drug dealing.

The other source of crime data in Mexico is the Office of the President. In this case, the data are mainly collected by the police and armed forces. An advantage of this dataset is that it is specifically focused on drug-related crime. However, mainly because of the time span that it covers, we prefer the SINAIS database to the Office of the President's database. The latter dataset covers a shorter period: from December 2006 to September 2011. As our estimations run from January 2008 to December 2011,[12] we would initially be missing data for just one quarter (from September 2011 to December 2011). Additionally, in this paper we use cumulative homicide rates (for the preceding 6-, 12- and 24-month periods) as the causal variable of interest, and we cannot obtain the cumulative 24-month rate using the Office of the President's database for the entire period for which we have data on housing prices.

Nevertheless, as can be seen in Figure 3, the correlation between the two sources is almost perfect. Thus, estimating the effect of total crime or drug-related crime can be expected to generate similar results. In Section 5.2, we show that the estimates and levels of statistical significance derived from the two databases are very similar.

Figure 3. Monthly Drug-Related Homicide Rate and Total Crime Rate in Mexico



Source: National Health Information System (SINAIS) and the Office of the President, Mexico.

[12] The SINAIS database covers the period from 2002 onward, but we are limited by the Housing Valuation database, which covers the period from 2008 onward.

3.2 Housing Price Data

By law (*Ley de Transparencia y Fomento a la Competencia en el Crédito Garantizado,* 2005), an official appraisal must be made of the property put up as collateral for *all* collateral-backed mortgages that are granted by financial intermediaries, and all of those appraisals must be reported to the Federal Mortgage Society (*Sociedad Hipotecaria Federal*—SFH), which is a government development bank. The appraisal has to be performed by an authorized appraiser (designated by SHF) on the basis of a specific, explicit, and detailed SHF procedure. According to the applicable rules, the appraisal must be based on sufficient information concerning at least six transactions involving similar houses on the local market. Violations of this rule can result in the revocation of the appraiser's license. Our data cover *all* the houses, apartments, and other real estate assets that were appraised in connection with a loan application.

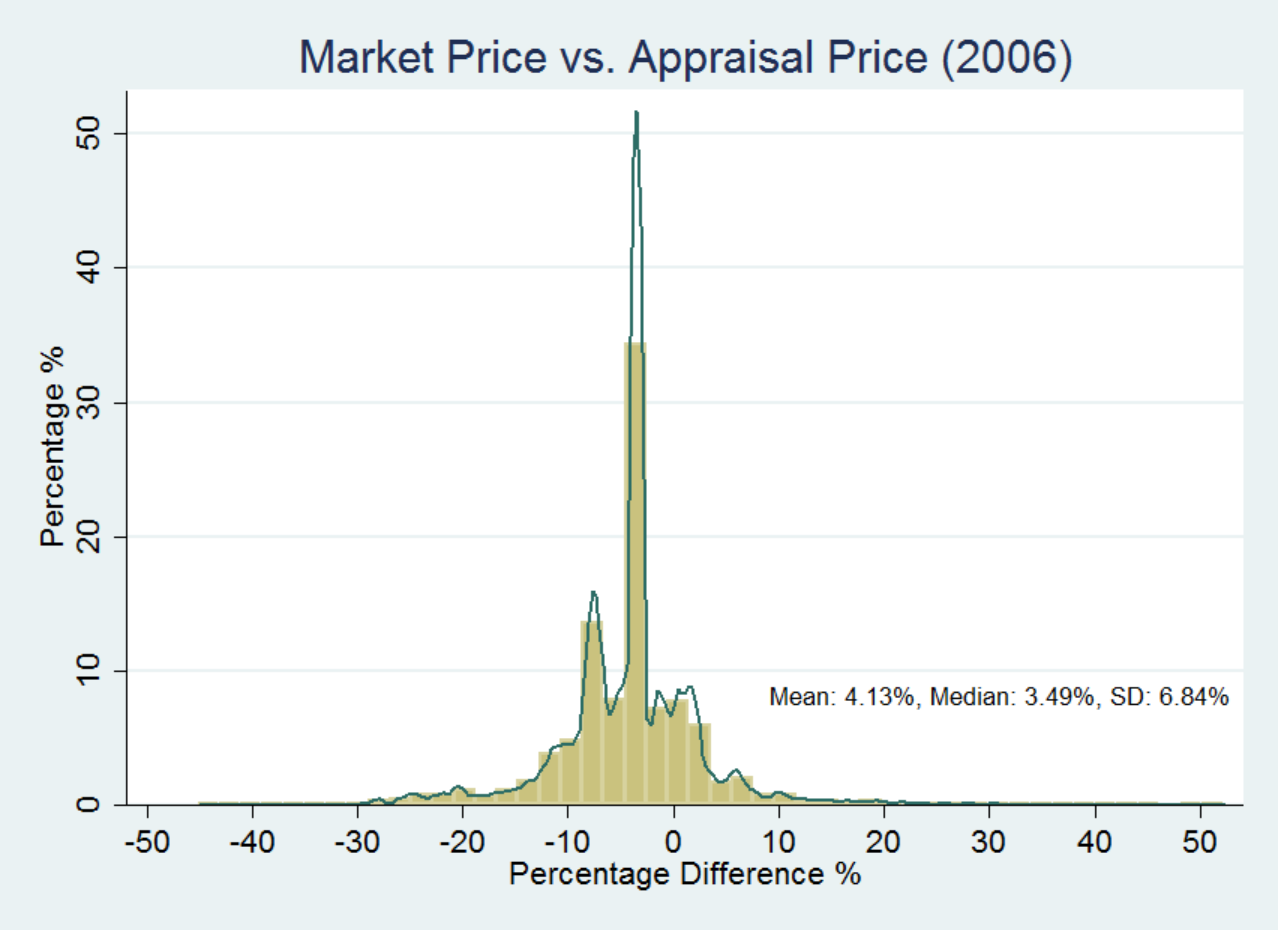
Our data on housing unit appraisals cover the four years between January 2008 and December 2011. In addition to the price variable—which is our main outcome—the dataset covers a number of dwelling characteristics, such as: size of the plot, built-up area, accessory areas, remaining life of the dwelling, age of the dwelling, number of bedrooms, number of bathrooms, number of parking places, whether the dwelling is an apartment or a house, its proximity to the city center, and classification of services, as well as codes for the bank, valuator, and municipality.

In our main analysis, we retain only those observations that provided GPS information at the locality level (that is, appraisals in localities identified by GPS coordinates). The reason for doing this is the need to control for the size of the locality, which is not possible to determine without knowing the exact location of the house. Although we lose some 40 percent of observations by doing this, in the robustness checks section we show that the results using either the entire database or the trimmed one are very similar. Even with the loss of observations, we are able to draw upon 1,370,676 observations of housing prices and 25 variables for each dwelling.

It is important to clarify that the housing prices in our dataset are not final price transactions but rather appraisals, which are purportedly based on current market prices. A skeptical reader might claim that appraisal values may not actually be closely correlated with market prices. We have compelling evidence that shows that appraisal prices are strongly correlated with market prices. Although we do not have data on market prices for multiple years,

we have data for 2006.[13] Figure 4 shows the distribution of percentage differences between market and appraisal values (as a percent of the market price) for the data for 2006. The median difference is about 3.5 percent. We also find that, controlling for city fixed effects, the mean difference between appraisal and market prices is close to 0, and the variability in actual prices explains about 93 percent of the variability in the appraisal prices. This shows that the appraisal valuations closely track market prices.

Figure 4. Difference between Market and Appraisal Prices



Source: Federal Mortgage Society (SHF), Mexico.

[13] Systematic data on appraisals begins in 2008. However, for 2006, we obtained a dataset with a sample of appraisals (and market prices) from one of the most important mortgage lenders (Infonavit), with a coverage of 50 municipalities (our dataset covers more than 1,100 municipalities). The dataset does not contain as many house characteristics as our dataset, but the valuation methods are the same.

3.3 Final Dataset

We merged the two datasets (homicides and appraisals) using municipality and year-month as the matching variables. The merged dataset comprises 1,370,367 dwellings in 1,165 municipalities (out of a total of 2,445 in Mexico) on a monthly basis from January 2008 to December 2011.

Dwellings are the main unit of analysis, and we have 25 variables for each one. Each house can be associated with the cumulative crime rate for the municipality in which the house is located. On average, there are 1,176 appraisals per municipality (adding up the four years of the sample), 28,549 appraisals for each of the 48 months included in the period of analysis, and 24.5 appraisals for each municipality-month.[14] Table 1 provides descriptive statistics. Having a dataset that includes a considerable number of dwelling characteristics allowed us not only to include a large number of relevant controls in our regression, but also to analyze the differential impacts on housing prices for poor and non-poor segments of the population.

[14] We have 48 months and 1,165 municipalities. Thus, we have 55,920 different municipality-months. Each of those municipality-months corresponds, on average, to 24.5 home appraisals (the observation unit).

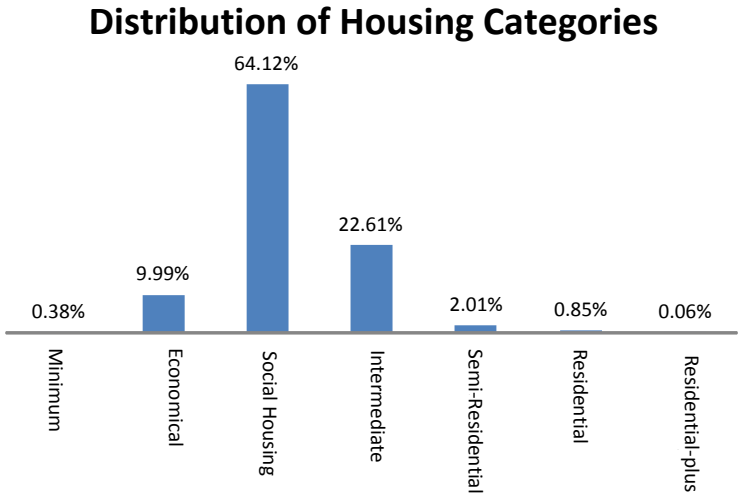
Table 1. Descriptive Statistics[15]

Variable	# Obs.	Min	Max	Mean	SD	Description
ln_housevalue	1,370,767	20,020	9,998,452	503,436	557,589	Official appraisal of the house or apartment, in pesos - log
ln_homicides (6 months)	1,370,767	0	2,309	66	208	Homicides: 6 months (cumulative rate) -log
ln_homicides (12 months)	1,370,767	0	3,761	121	381	Homicides: 12 months (cumulative rate) -log
ln_homicides (24 months)	1,370,767	0	6,550	201	616	Homicides: 24 months (cumulative rate) -log
ln_size_plot	1,370,767	18	3,000	137	205	Size of the plot -log
ln_built-up...area	1,370,767	30	2,817	73	52	Built-up area - log
ln_area_accessory	1,370,767	0	2,493	3	13	Accessory Area - log
ln_rem_lifespan	1,370,767	1	1,200	680	119	Remaining months of useful life - log
ln_antig	1,370,767	1,900	2,011	2,005	9	Years since construction finished - log
ln_number_BR	1,370,767	0.00	10.00	2.12	0.78	Number of bedrooms - log
ln_number_bath	1,370,767	0.00	10.00	1.25	0.58	Number of bathrooms - log
ln_number_parking	1,370,767	0.00	30.00	1.06	0.51	Number of parking spaces - log
small_loc	1,370,767	0.00	1.00	0.51	0.50	Locality has a population of less than 50,000
Lower-income	1,370,767	0.00	1.00	0.11	0.30	Luxuriousness of the house/apartment: "Economical" (bottom 10% of the sample is "lower-income") - log
has_telephone	1,370,767	0.00	1.00	0.53	0.50	House or apartment has telephone
house_condo	1,370,767	0.00	1.00	0.26	0.44	House within a condo
apt_condo	1,370,767	0.00	1.00	0.09	0.29	Apartment within a condo
urban_proximity: central	1,370,767	0.00	1.00	0.04	0.20	House or apartment in urban area
urban_proximity: intermediate	1,370,767	0.00	1.00	0.28	0.45	House or apartment near urban area
urban_proximity: peripheral	1,370,767	0.00	1.00	0.49	0.50	House or apartment in the periphery of an urban area
urban_proximity: outskirts	1,370,767	0.00	1.00	0.18	0.38	House or apartment near the outskirts of an urban area
urban_infra_3_services	1,370,767	0.00	1.00	0.05	0.21	House or apartment block has access to: potable water, plumbing and street lighting
urban_infra_5_services	1,370,767	0.00	1.00	0.78	0.41	House or apartment block has access to: potable water, plumbing, street lighting and paved roads
urban_infra_7_services	1,370,767	0.00	1.00	0.16	0.36	House or apartment block has access to: potable water, plumbing and street lighting, paved roads, natural gas and private security
house_class_intermediate	1,370,767	0.00	1.00	0.22	0.42	Comfort of the house or apartment: classified as "intermediate"
house_class_semi_res	1,370,767	0.00	1.00	0.02	0.14	Comfort of the house or apartment: classified as "semi-residential"
house_class_residential	1,370,767	0.00	1.00	0.01	0.09	Comfort of the house or apartment: classified as "residential" (more comfortable than semi-residential)
dummies: Peri	1,370,767					Dummies: qualified professional who made the appraisal
dummies: Bank	1,370,767					Dummies: bank (lender)

[15] Descriptive statistics are not in logs.

Figure 5 sets out the categories of dwellings (low-income, middle-income, high-income, etc.) based on the quality of their infrastructure. In our sample, 3 percent of the dwellings are classified as high-income, 22 percent as middle-income, 64 percent as "social housing" and 10 percent as economical, or low-income.[16,17]

Figure 5. Housing Classification



Source: Federal Mortgage Society (SHF), Mexico.

In our estimations, we define "low-income dwellings" as those that fall into the "minimum" or "economical" categories of the appraisal methodology. Low-income housing, which comprises about 10 percent of the sample, has substandard infrastructure (i.e., no access to electricity, water, or transport) and was not built to conform to any architectural plan (these

[16] This classification is the one used by the Federal Mortgage Society (SHF). Its Intermediate Category, for instance, corresponds to housing that has rooms that are differentiated by use, such as living rooms, bedrooms, and kitchens. According to this classification, low-income housing is built in groups, with identical prototypes, but has adequate infrastructure.

[17] There is no straightforward way to compare these housing characteristics to those used in the national census because the definition of "low-income housing" that we use is based entirely on the SHF classification. However, it is possible to compare a few of the housing characteristics recorded in our database with the census averages. Specifically, in our data, dwellings with telephones represent 53 percent of the total vs. 43 percent in the census results. The distribution for the number of bedrooms is the following (our data, census data): 1 BR (20%, 35%), 2 BR (53%, 40%), 3 BR (23%, 20%), 4BR (2%, 4%), 5 BR (0.4%, 0.8%) and 6 or more BR (0.2%, 0.3%).

dwellings are usually "informal" constructions). As shown in Table 2, low-income dwellings have fewer bedrooms and bathrooms, are older, smaller, have less useful life remaining, afford access to fewer services, and in general have infrastructure of poorer quality.

Table 2. Lower- and Upper-Income Categories

	Upper-Income	**Lower-income**
Number of Bedrooms	2.15	1.87
	(0.76)	(0.84)
Number of Bathrooms	1.26	1.09
	(0.6)	(0.35)
Years since Constructed	4.44	7.24
	(8.99)	(10.44)
Plot Area (Constructed)	73.82	66.01
	(53.24)	(45.62)
Months of Useful Life Remaining	688	624.88
	(117.01)	(119.7)
Has Telephone	0.54	0.44
	(0.49)	(0.50)
Infrastructure: Poor (*)	0.046	0.17
	(0.21)	(0.37)
Infrastructure: Acceptable (**)	0.95	0.82
	(0.21)	(0.37)

* Includes housing with no services and housing with access to potable water, plumbing and street lighting.

** Includes housing with access to potable water, plumbing, street lighting and paved roads and housing with access to natural gas and private security.

4. Literature Review

There is quite an extensive body of economic literature about crime and its determinants, much of which most likely emerged in response to the increase in crime in the United States in the 1970s and its precipitous decline in the 1990s. Most of these studies focus on property crime. Levitt (2004) provides a cogent review of the *causes* of the decline in crime in the 1990s in the United States and documents the fact that, as demonstrated in the literature, economic conditions—measured by unemployment or wages—have little impact on property crime and virtually none on violent crime. He finds that better policing and higher incarceration rates

largely explain the decline in crime in the 1990s. Corman and Mocan (2000) use a long time series to study the relationship between homicides and drug use and conclude that they are unrelated. None of the studies mentioned by Levitt relate to DRHs committed by DTOs.

To our knowledge, Dell (2012) is the first to look at the causal determinants of DTO killings. Her analysis is relevant here because it shows that in Mexico, in the period under study, government-driven policy causally explains the DRH rate without reference to economic causes. She exploits a regression discontinuity design in mayoral elections and shows that when a mayor from the PAN party (the party of President Calderón) wins in a close election, the average probability that a drug-related homicide will occur increases by 9 percent in any given month during the 5 months following the time that the person takes office. Starting from a baseline rate of 5 percent per month, this is a huge effect.

The literature regarding the *effects* of crime on economic activity is scant but growing. Abadie and Gardeazabal (2001) show that, relative to a synthetic control group in the absence of terrorism in the 1980s and 1990s, per capita GDP in the Basque country declined by about 10 percent. Their study is the first to document large macroeconomic effects of violence.

At a more micro level, three widely cited papers, which look at the effects of crime on housing prices, are relevant to our study. These papers focus mainly on identifying the causal effects of violence, since crime may not be exogenous in an equation of the determinants of housing prices. In one of the first papers to address this issue, Gibbons (2004), using data from London, looks at the effect of criminal damage to dwellings on residential property values. To overcome the potential endogeneity of crime, he uses the spatial lags of crime and the number of reported offenses against non-residential properties as instruments. He concludes that an increase of one standard deviation in property damage decreases property values by 10 percent.

Linden and Rockoff (2008) study the effect of the arrival of a sex offender in a U.S. neighborhood. They exploit a credible identification strategy by using panel data on housing prices and comparing them before and after a sex offender takes up residence in a specific neighborhood. By using detailed location data, they can measure how the effect varies with distance from the house and find that, although prices of adjacent houses decline by 12 percent, there is no change for houses located outside of a 0.1-mile radius of a sex offender's residence.

Besley and Mueller's study (2012) is the most relevant of all for our purposes. They study the effect of peace on housing prices in Northern Ireland in the 1990s after the truce between the

Irish Republican Army and the Loyalists was called. They use within-region variations over time in conflict-related homicides and a housing price index for 11 regions in Northern Ireland, with quarterly data from 1984 to 2009. Their study uses murders to estimate a latent Markov process of peace/violence in which states are defined endogenously, which they then use to construct an estimate of the present value of deaths as a function of murders for each region. This estimate is then used in a structural model of the peace process. The structural model has the advantage of incorporating the persistence of violence into the estimation of its cost. They find that peace leads to an increase in housing prices of between 1.3 and 3.5 percent on average, although the effect is many times larger in more violent regions. Using a benchmark OLS regression, with region and time fixed effects (an approach more akin to ours), they find that a one standard deviation decrease in assassinations is associated with an increase in housing prices of from 0.8 to 1.4 percent.

Our paper contributes to the literature in several respects. First, to our knowledge this is the first paper that explores the effect of DTO violence. This is surprising, given that drug policy and its costs and benefits are an issue of concern to many countries and that DTOs are leading to more deaths than many recent wars have. DRHs may have a different pattern of effects from those of terrorism, since they are not committed in pursuit of the political objective of overthrowing a government. One advantage that we share with Besley and Mueller (2012) is that, in the case of homicides, measurement error is less likely to be a serious problem than in the case of other types of crime. Second, our source of variation in violence is disaggregated at the municipality level (we use 1,165 municipalities), allowing us to have better controls for the determinants of crime by using municipality fixed effects, while at the same time controlling for a large set of characteristics of individual dwellings. This limits the attribution of changing prices to changes in the pool of dwellings for sale. Third, and importantly, there is substantial variation across time and municipalities in the timing and the intensity of violence. Spikes in violence are probably uncorrelated with trends in economic variables, which typically move more smoothly. We identify the effects of violence as municipality-specific deviations from trends. Furthermore, variation in DRHs is likely driven by government attacks on DTOs, and we believe that this is unlikely to be correlated with changes in housing prices that are not due to the incidence of DRHs. Finally, the geographical coverage of the data gives us confidence that it has substantial external validity and that it is representative at the municipality level.

We are able to at the effect not only of killings but also of persistent violence on housing prices, similar to what Besley and Mueller (2012) did by modeling the peace process using the history of killings in the region in a Markov switching model. We complement their findings in the sense that we can also look at the distribution of the effects according to socioeconomic status, which is a very important policy issue.

It is believed that because affluent people are more mobile and have more resources to protect their property, the impact of violence may primarily be borne by the poor. There is some evidence to support this conjecture: using survey data from Mexico to assess the level of coercion exerted by DTOs on different groups, Cayeros et al. (2011) show that the extent of extortion by DTOs is greater among recipients of the *Oportunidades* Program's conditional cash transfers, which are given to the poor. We also find that the impact of violence on poor people is greater—the decrease in housing prices is concentrated among low-quality dwellings. This is in line with the results of Di Tella et al. (2010), who find that burglaries of poor people's dwellings increased by about 50 percent more than those of affluent people's dwellings during the crime wave that hit Argentina in the 1990s and early 2000s. However, the channel through which this differential effect operates is different. In our case, the greater presence of violence in poor neighborhoods is what represents a dis-amenity that leads to a sharper reduction in the price of housing in those locations. In Di Tella et al. (2010), the rich are better prepared to cope with an increase in crime because they can protect themselves (by, for example, hiring private security). As a consequence, crime is displaced to poorer areas. Di Tella et al. (2010) find that burglary rates are much higher in low-income areas but that there is no significant difference in the number of street robberies, an offense which affects the poor and the rich more or less alike.

5. Econometric Models and Identification Strategy

Our goal is to measure the causal effect of DRHs on housing prices. Simply regressing housing prices on DRHs is likely to be problematic, since there may be problems of reverse causality (i.e., that falling home prices may lead to a change in neighborhood composition, attracting more crime-prone people) or of omitted variables that influence crime and prices simultaneously. For example, higher unemployment may depress housing prices and drive up crime rates at the same time.

Our identification strategy exploits the panel structure of our data by conditioning on municipality fixed effect, period effects and municipality-specific linear time trends. Our basic empirical model is as follows:[18]

$$\log(P_{ijt}) = \alpha_t + \gamma_j + t\gamma_j + \delta X_{ijt} + \beta \log(Cum.Hom._{jt}) + \varepsilon_{ijt} \quad (1)$$

where $log(P_{ijt})$ is the logarithm of the price of dwelling *i* in municipality *j* in month *t*. α_t, γ_j are the fixed effects which control for time trends and those differences across municipalities that are fixed over time. We include a set of 25 dwelling and locality characteristics (X_{ijt}) including indicator variables for the appraiser and for the banks to which the loan application was submitted. Additionally, we control for municipality-specific monthly linear time trends ($t\gamma_j$).

The causal variable is the cumulative number of homicides in municipality *j* at time *t*. The cumulative number of homicides is the sum of those incidents over the previous 6, 12, and 24 months. These figures provide a more stable measurement that can then be used to characterize dangerous places and to take into account potential lags in the effect of crime on housing prices. We do not expect that a mere spike in crime for a month or two, even if very large, could affect housing prices. It is more permanent changes in the amenities of houses that would be reflected in their prices. Standard errors are clustered at the level of the municipality.

The causal effect of homicides on housing prices comes from within-municipality-month variations in cumulative homicides and housing prices after controlling by a large number of housing characteristics and other determinants of the house price appraisals. In other words, to identify the effect of interest to us here, we assume that changes in cumulative homicide rates are strictly exogenous in equation (1).

Equation (1) controls by municipality characteristics fixed over the four years of the study. For example, local amenities (such as good schools) may influence housing prices and are captured by the municipality fixed effects. Secular trends in housing prices due to changes in macroeconomic or seasonal conditions are controlled by the period fixed effects. We also include linear trends in the model. This would take into account the presence of differential trends in prices across municipalities due to unobserved local time-varying effects. Finally, we also

[18] If we were to use per capita homicides instead of total homicides, we would have to use a linear approximation of the population based on 2005 and 2010 census data (at the municipality level). This does not make any difference to our specification, in which we include municipality and period fixed effects, as well as municipality-specific linear trends.

control for a large set of observable housing characteristics (as well as characteristics of the bank and individual appraiser that perform the valuation of the house).

The validity of our identification strategy could be undermined if changes in homicide rates are also driven by economic factors the influence housing prices. This does not seem to be the case, however. There is evidence that DTOs operate at a regional level (i.e., their area of operations thus encompass many municipalities) and that their behavior is not driven by the economic situation of the municipality (Dell, 2012),[19] which reinforces our identification strategy.

To find further evidence that the timing and intensity of violence do not seem to be driven by the economic situation in a given municipality, we investigate the link between formal employment and crime at the municipality level. We use a dataset containing a municipality-monthly measure of *all* formal employment in Mexico prepared by the Mexican Social Security Institute (*Instituto Mexicano del Seguro Social*—IMSS) and the SINAIS database on crime.[20] Table 3 shows the result of preparing estimates using the following equation for all municipalities for which we have homicide and employment data:

$$\log\left(Cum.Hom._{jt}\right) = \alpha_t + \gamma_j + \beta Formal\ employment_{tj} + \varepsilon_{tj} \quad (2)$$

The correlation between homicides and employment is not statistically different from zero, which is consistent with our identifying assumption that the type of crime being analyzed is not related to the labor market or, more broadly, to economic variables.[21,22]

[19] According to Dell (2012): "Over 85 percent of the drug violence consisted of people involved in the drug trade killing each other" either as a way of extracting revenge or as a way of expanding their territories. She also notes that the killings are especially frequent after one side is weakened by government intervention.

[20] We would like to thank Judith Frias for providing these data, which are even more reliable than survey data because, since they come from a census of the formal employment sector, they are representative at the level of the municipality and have no measurement error associated with the definition of formal employment.

[21] We present the estimations for two periods: 2006-2008 (prior to our estimation period for the effect of crime on housing prices, which starts in 2008) and 2006-2011, which encompasses the entire crime wave.

[22] We ran a similar regression using unemployment rate as the independent variable. As expected, we did not find any significant relationship between unemployment and crime for the periods 2005-2010 and 2005-2008. We did not have unemployment data at the municipality level for 2011.

Table 3. Employment and Homicides

	Log Per Capita Homicides	Log Homicides	Log Cum. Homicides: 6 months	Log Cum. Homicides: 12 months	Log Cum. Homicides: 24 months
2006-2008					
Log (Employment Rate)	0.0015	0.0027	0.0029	-0.002	0.007
	(0.003)	(0.005)	(0.008)	(0.010)	(0.012)
Observations	39,888	39,888	39,888	39,888	39,888
R-Squared	0.98	0.97	0.97	0.97	0.97
2006-2011					
Log (Employment Rate)	0.0019	-0.005	0.002	0.007	0.014
	(0.002)	(0.004)	(0.006)	(0.007)	(0.009)
Observations	127,734	127,734	127,734	127,734	127,734
R-Squared	0.94	0.94	0.94	0.94	0.94

Clustered standard errors in parentheses (municipality), quarter and municipality fixed effects. Quarterly averages.
*** p<0.01, ** p<0.05,
*p<0.1

Another potential concern with regard to our identification strategy, which is common to all studies that use home sale prices, is that we are only considering houses that have been appraised for sale. If, for example, richer people who own better houses were to decide to sell their homes so that they can move away from a high-crime area, and the regression model would not control for that, we would underestimate the negative impact of violence on housing prices. To limit this statistical nuisance, we control for an unusually large set of housing characteristics. These characteristics alone can account for up to 92 percent of the variation in prices (Table 4) when period effect and fixed effects by municipality, bank, and appraiser are included. This considerably mitigates concerns regarding selection bias of the houses that enter the market by municipality and over time.

Table 4. Price Variance Explained by Controls

	Log (Price)		
	(1)	**(2)**	**(3)**
Municipality Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	Yes
Appraiser Fixed Effects	No	Yes	Yes
Property Characteristics Controls	No	No	Yes
N	1,370,767	1,370,767	1,370,767
R-Squared	0.39	0.62	0.92

* Clustered standard errors in parentheses (municipality).
*** p < 0.01, ** p < 0.05, * p < 0.1

Moreover, our sample covers all the appraisals—homes belonging to low-income and high-income persons—that were done as part of the home mortgage application process. In Mexico, even the poorer segments of the population apply for and obtain mortgage loans: about 65 percent of our sample is made up of loans furnished by Infonavit, Fovisste or Cofinavit, which are government institutions that subsidize loans for the poorer segments of the population.[23] This unique feature of our dataset allows us to investigate the distributional effect of DRH.

Finally, since we are interested in the differential impact that crime may have on different socioeconomic groups, we also estimate an econometric specification which identifies the differential effect of crime on low-quality housing by interacting homicides with a low-quality housing dummy. However, there may be factors other than a sudden increase in crime that affect the poor by driving down low-quality housing values. Therefore, in order not to confuse this differential effect with a differential secular trend in the price of houses by socioeconomic status, we also include in the model a differential secular trend for lower-class houses and estimate the following empirical model:

$$\log(P_{ijt}) = \alpha_t + \gamma_j + t\gamma_j + \emptyset LowQuality_{ijt} + \alpha_t LowQuality_{ijt} + \delta X_{ijt} + \\ + \beta \log(Cum.Hom.s_{jt}) + \theta LowQuality_{ijt} \log(Cum.Hom._{jt}) + \varepsilon_{ijt} \quad (3)$$

[23] The Infonavit loan is designed for members of the population who earn less than 6,000 Mexican pesos per month (less than US$500).

6. Main Results

This section presents our main results based on both the SINAIS data and the data from the Office of the President. Columns 1 to 3 show the estimates for equation (1) for different cumulative periods (6, 12, and 24 months), and columns 4 to 6 do the same for equation (3).

Table 5. The Effect of Homicides on Housing Prices

	(1) Cumulative Homicides 6 months	(2) Cumulative Homicides 12 months	(3) Cumulative Homicides 24 months	(4) Cumulative Homicides 6 months	(5) Cumulative Homicides 12 months	(6) Cumulative Homicides 24 months
Cumulative Homicides (log)	-0.0008	0.0030	0.0013	0.0002	0.0042	0.0025
	(0.0019)	(0.0025)	(0.0040)	(0.0020)	(0.0026)	(0.0041)
Cumulative Homicides (log) * Low Quality				-0.0123***	-0.0128***	-0.0130***
				(0.0033)	(0.0032)	(0.0030)
Total Effect: Lower Quality				-0.0121***	-0.0086**	-0.0105**
Property and Locality Characteristics	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES
Bank Fixed Effects	YES	YES	YES	YES	YES	YES
Appraiser Fixed Effects	YES	YES	YES	YES	YES	YES
Municipality Fixed Effects	YES	YES	YES	YES	YES	YES
Municipality Trends	YES	YES	YES	YES	YES	YES
Interaction: Month Effect * Lower Income	NO	NO	NO	YES	YES	YES
Observations	1,370,767	1,370,768	1,370,769	1,370,770	1,370,771	1,370,772
R-Squared	0.93	0.93	0.93	0.93	0.93	0.93

Clustered standard errors in parentheses (municipality)

*** p<0.01, ** p<0.05, *p<0.1

We find a zero average effect on housing prices (Table 5). However, we do find a negative impact on the prices of low-quality housing. A 100 percent increase in homicides is associated with a decrease in housing prices of between -0.9 and -1.2 percent, depending on the specification adopted. While Besley and Mueller (2012) find that a decrease of one standard deviation in homicides leads to a 0.8 to 1.4 percent increase in prices (when using an OLS benchmark with region and time fixed effects), we find a price reduction of between 3 and 4 percent as a result of DRHs in Mexico, but only for poor-quality housing.

Our results indicate that violence, as reflected in homicides, has a regressive distributive effect, since it affects poorer individuals more than richer ones. This result is consistent with a short previous literature claiming that the effects are different for the rich and the poor and that wealthier people can either flee from violent places or invest in technologies that will reduce the chances that they will fall victim to crime (Di Tella et al., 2010; Levitt, 1999).

The size of the effect that we find is quite large, considering that some municipalities experienced sharp increases in crime. Crime increased more than 200 percent nationally between 2006 and 2011. Table 6 shows that the cumulative increase in crime was above 100 percent for 48 municipalities and, in some, it was much higher. In Monterrey, for instance, homicides increased by more than 2,500 percent, and several municipalities experienced tenfold increases. Taken at face value and extrapolating at the national level, our results would indicate that from 2006 to 2011 housing prices for the dwellings of poor people decreased by 2.5 percent, while municipalities such as Monterrey experienced a decrease in prices several orders of magnitude larger. Given that a home is one of the most important assets that families own, especially among the poor, this decline represents a substantial loss of wealth, and this loss is concentrated among the poorer segments of the population.

Table 6. Municipalities with a More Than 100 percent Increase in Crime in 2007-2011**

Increases in Crime by Municipality*	Total Crime (2007)	Total Crime (2011)	Var. 2001-2007 (%)	Difference (2011-2007)
Valle Hermoso	1	127	12,567	126
Delicias	1	79	7,767	78
Santiago	1	60	5,900	59
Torreón	12	635	5,189	623
Tepic	5	261	5,127	256
Cárdenas	1	49	4,833	48
Colima	1	47	4,567	46
Guadalupe y Calvo	1	43	4,167	42
Yurécuaro	1	39	3,767	38
Pánuco	2	72	3,500	70
Cuautitlán Izcalli	1	33	3,233	32
Saltillo	2	67	3,233	65
Montemorelos	1	31	2,967	30
Apodaca	4	119	2,867	115
Allende	1	29	2,833	28
Cadereyta Jiménez	3	85	2,744	82
Hidalgo del Parral	4	103	2,467	99
Cuautla	1	23	2,167	22
Tampico	4	84	2,000	80
Victoria	3	63	1,989	60
Durango	25	520	1,980	495
Zapopan	7	145	1,976	138
Tlaquepaque	3	61	1,944	58
Salamanca	1	20	1,900	19
Fresnillo	1	20	1,900	19
Benito Juárez	1	19	1,767	18
Temixco	2	37	1,767	35
El Fuerte	3	56	1,767	53
Villa de Álvarez	1	19	1,767	18
Acaponeta	1	19	1,767	18
Chihuahua	30	536	1,687	506
Guadalupe	10	175	1,647	165
Puente de Ixtla	1	17	1,633	16
Zamora	1	17	1,633	16
San Marcos	1	17	1,633	16
Toluca	1	17	1,633	16
Cuautla	1	21	39	18
Iztacalco	1	27	57	30
Irapuato	1	24	42	18
Tultitlán	1	36	78	42
Hermosillo	1	45	84	39
Chalco	1	51	57	6
Iztapalapa	1	168	324	156
Zamora	1	33	42	9
Centro	1	30	45	15
San Juan Bautista Tuxtepec	1	21	39	18
Tijuana	1	258	534	276
Apatzingán	1	60	105	45

* Includes only municipalities with a crime rate different from 0 in 2007. As data for the whole of 2011 are not available, the figure for that year is based on an extrapolation of the crime rates for the first 9 months.
** The terms “crime” and “homicide” are used interchangeably.

Source: Office of the President.

6.1 Ancillary Results

We now present some ancillary evidence consistent with both our empirical findings and their interpretation. First, we show that the poor display stronger negatives of crime in response to the incidence of DRH experienced at the municipality level in the recent past. Second, we test whether the poor are more likely to have moved in the recent past as a reaction to municipality-level incidence of DRH experienced recently. This evidence should be considered as suggestive and not taken as causal, since it only exploits cross-sectional variability.

To provide evidence of the first hypothesis, we rely on data gathered from the 2012 National Victimization and Public Safety Survey[24] and combine it with crime data used in our main econometric analysis. We estimate the following regression model:

$$Victimization_{ij2012} = \partial + \emptyset PoorHH_{ij2012} + \beta \log\left(Cum.Hom_{j2008-2011}\right) + \theta PoorHH_{ij2012} \log\left(Cum.Hom_{j2008-2011}\right) + \varepsilon_{ij} \quad (4)$$

where $Victimization_{ij2012}$ corresponds to the reporting of victimization by household i in municipality j according to the 2012 survey of victimization, $PoorHH_{ij2012}$ is a dummy variable that indicates whether household i in municipality j is poor in 2012 (when the survey was conducted), and $log\left(Cum.Hom_{j2008-2011}\right)$ is the log of the homicides accumulated during the period 2008-2011 in municipality j. The parameters of interest are β (impact of crime on the incidence of victimization) and $(\beta + \theta)$ (impact of crime on the incidence of victimization of poor households).

The Victimization Survey does not include information about income. However, it includes a few questions regarding the employment status and education of the household head. Using that information, we constructed the variable $PoorHH$, using the following criteria: a household is poor if the head is i) unemployed and has less than complete high school education (less than six years of primary school plus three years of high school); ii) "employed" with no salary; or iii) self-employed and did not complete high school.[25]

[24] Encuesta Nacional de Victimización y Percepción sobre Seguridad Pública (ENVIPE), INEGI.

[25] Although we report one particular criterion to determine poverty status, we tried five combinations of employment-status and maximum-education of the Household Head to get five different criteria to classify households into poor and non-poor. The results of the analysis were almost identical irrespective of the criteria adopted. According to our criteria, about 23 percent of the households in the survey were classified as poor.

Table 7 shows the results for four variables related to the level of victimization of each household: insecurity index, feel safe at home, knowledge of drug-dealing, and worried about drug-dealing or insecurity.[26]

Table 7. Effect on Victimization[27]

	(1)	(2)	(3)	(4)
	Insecurity Index	**Feel Safe at Home**	**Knowledge of Drug-Dealing**	**Worried about Drug-Dealing or Insecurity**
Cumulative Homicides 2008/2011 (log)	0.0059***	-0.0089***	0.0148***	0.0030
	(0.0017)	(0.0027)	(0.0043)	(0.0039)
Poor HH	-0.0192***	0.0220**	-0.0443***	0.0222
	(0.0064)	(0.0101)	(0.0133)	(0.0159)
Cumulative Homicides (log) * Poor HH	0.0048***	-0.0057***	0.0100***	0.0048
	(0.0013)	(0.0021)	(0.0027)	(0.0033)
Total Effect on Non-poor	0.0059***	-0.0089***	0.0148***	0.0030
Total Effect on Poor	0.0107***	-0.0146***	0.0248***	0.0078**
Observations	70,937	70,828	70,937	70,937
R-squared	0.0065	0.0025	0.0065	0.0016

Clustered Standard Errors in Parentheses (municipality)

*** p<0.01, ** p<0.05, *p<0.1

The results are conclusive: for all of the variables considered, poor households report a considerably higher impact of crime. The impact on the insecurity index is about twice as large for the poor, and it is 65 percent larger on the "feel safe at home" and the "knowledge of drug dealing in the neighborhood" questions. Moreover, poor households rank insecurity and drug dealing as their main concerns more frequently as a consequence of crime, whereas, in the case

[26] "Insecurity Index:" from 0 (minimum) to 1 (maximum) is the proportion of "yes" answers to 17 questions about the household's knowledge about illegal activities in the neighborhood, such as: "Have you heard shots near your house?" "Feel Safe at Home:" Answered "yes" to the question: "Do you feel safe at home?" "Knowledge of Drug-Dealing": Answered "yes" to the question "Do you know if there is drug dealing near your home?" "Worried about drug dealing or insecurity": 1 if the person mentioned drug dealing or insecurity as one of their three main concerns, 0 otherwise.

[27] The original Victimization Survey (2012) has 83,483 observations. About 12,600 are not considered in our analysis because we restrict the sample to the municipalities that have data on crime and on appraisals. In other words, we restrict the analysis to our main sample. Unfortunately, not all of the municipalities included in our main database are included in the Victimization Survey. Therefore, the victimization analysis covers approximately 70 percent of the municipalities in our main database.

of non-poor households, crime does not seem to modify significantly their ranking of main concerns. This evidence suggests that crime has a big differential effect for the poor in terms of their perception of security.

To provide evidence on the second hypothesis, we also rely on the 2012 Victimization Survey and estimate regression (4), but using "new home" as the dependent variable, which takes a value of 1 if the household has been living in the surveyed house for less than a year and 0 otherwise.

Table 8. Effect of Victimization on Migration

	New Home
Cumulative Homicides 2008/2011 (log)	0.0048***
	(0.0017)
Poor HH	-0.0419***
	(0.0066)
Cumulative Homicides (log) * Poor HH	0.0025*
	(0.0014)
Total Effect on Non-Poor	0.0048***
Total Effect on Poor	0.0073***
Observations	77,912
R-squared	0.0038

Clustered Standard Errors in Parentheses (municipality)

*** p<0.01, ** p<0.05, *p<0.1

The results in Table 8 suggest that, although rich and poor households tend to move more in those municipalities where the crime grew the most, the effect is more than 50 percent larger in the case of the poor households. Interestingly, poor households in municipalities not affected by crime appear to move less than non-poor households. This result holds despite the fact that migration is not fostered by DHR. Altogether, this empirical evidence is consistent with the

interpretation we advanced for our main results, namely, that DHR affects the amenities of the poor disproportionately more in the municipalities that were afflicted by that type of violence, which tended to decrease home prices of the poor in those municipalities as a function of the intensity of the crime shock.

6.2 Robustness Checks

In the interest of robustness, we have redone our main estimations using different data and specifications. First, as explained above, our main database only includes those houses that can be geo-localized. This is necessary to control for the size of the locality, which cannot be otherwise determined. To show that our results do not depend heavily on this, in Table 9 we show the results of our main regressions—equations (1) and (3)—using the whole database (and, thus, not controlling for the size of the locality). As expected, the general results are very similar: the effect is zero for the high-quality houses, and negative and significant for the low-quality houses in the specifications with 6 and 24 months. Only in the 12-month specification does the total effect loss turn out not to be significant at conventional levels of statistical significance, with a p-value of 0.14.[28]

[28] Apart from the observations that do not have geo-localization data, we include in this specification about 2,000 observations (0.08 percent of the sample) that have locality identification but were excluded from our main dataset because they seemed to be repeated observations.

Table 9. The Effect of Homicides on Housing Prices (Robustness)

	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative Homicides 6 months	**Cumulative Homicides 12 months**	**Cumulative Homicides 24 months**	**Cumulative Homicides 6 months**	**Cumulative Homicides 12 months**	**Cumulative Homicides 24 months**
Cumulative Homicides (log)	0.0000	0.0026	0.0020	0.0009	0.0033	0.0020
	(0.0020)	(0.0027)	(0.0039)	(0.0021)	(0.0028)	(0.0039)
Cumulative Homicides (log) * Low Quality				-0.0095**	-0.0099**	-0.0102**
				(0.0045)	(0.0043)	(0.0040)
Total Effect: Lower Quality				-0.0086*	-0.0066	-0.0082*
Property and Locality Characteristics	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES
Bank Fixed Effects	YES	YES	YES	YES	YES	YES
Appraiser Fixed Effects	YES	YES	YES	YES	YES	YES
Municipality Fixed Effects	YES	YES	YES	YES	YES	YES
Municipality Trends	YES	YES	YES	YES	YES	YES
Interaction: Month Effect * Lower Income	NO	NO	NO	YES	YES	YES
Observations	2,279,492	2,279,492	2,279,492	2,279,492	2,279,492	2,279,492
R-Squared	0.919	0.919	0.919	0.918	0.919	0.919

Clustered Standard Errors in Parentheses (municipality)

*** p<0.01, ** p<0.05, *p<0.1

Second, we have redone these estimations using DRHs as the causal variable gathered from the database of the Office of the President. As noted above, these data are an independent source of information. Since DRHs have been the main driver of changes in homicide patterns in this period, it is to be expected that the use of this variable will yield the same correlation pattern as the one derived from the SINAIS database. Since in this case we have a shorter time series, we report results only for the cumulative 6- and 12-month DRH rates.

Table 10. The Effect of Homicides on Housing Prices
(Database of the Office of the President)
Log (Property Price)

	(1) Cumulative Homicides 6 months	(2) Cumulative Homicides 12 months	(3) Cumulative Homicides 6 months	(4) Cumulative Homicides 12 months
Cumulative Homicide Rate (log)	-0.00073	-0.0010	0.0002	-0.0001
	(0.0015)	(0.0017)	(0.0016)	-0.0019
Cumulative Homicides (log) * Lower-Quality			-0.0093***	-0.0096***
			(0.0034)	(0.0032)
Total Effect: Lower-Quality			-0.0091***	-0.0098***
Property and Locality Characteristics	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES
Bank Fixed Effects	YES	YES	YES	YES
Appraiser Fixed Effects	YES	YES	YES	YES
Municipality Fixed Effects	YES	YES	YES	YES
Municipality Trends	YES	YES	YES	YES
Interaction: Month Effect * Lower-Quality	NO	NO	YES	YES
Observations	1,320,015	1,320,015	1,320,015	1,320,015
R-Squared	0.93	0.93	0.93	0.93

Clustered standard errors in parentheses (municipality).
*** p<0.01, ** p<0.05, *p<0.1

As was to be expected, the results in Table 10 are almost unchanged. The effect of DRHs is concentrated among low-income housing, and the reduction in price is about 3 percent for a one standard deviation increase in DRHs.

Finally, we estimate our main regression, but without controlling for linear trends at the municipality level. In our principal specification, we preferred to include trends to take into account the presence of differential trends in prices across municipalities due to unobserved local time-varying effects. In any case, Table 11 shows that the results remain almost unchanged: excluding the linear trends does not modify the sign or significance of the effects. Therefore, the distributive effects of DRH that we found in our main specification are robust to removing the linear trends by municipality as control variables.

Table 11. The Effect of Homicides on Housing Prices
Excluding Municipality Linear Trends

	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative Homicides 6 months	**Cumulative Homicides 6 months**	**Cumulative Homicides 12 months**	**Cumulative Homicides 12 months**	**Cumulative Homicides 24 months**	**Cumulative Homicides 24 months**
Cumulative Homicide Rates (log)	-0.0066*	-0. 0051	-0.0053	-0.0040	-0.0088	-0.0074
	(0.0032)	(0.0038)	(0.0049)	(0.0051)	(0.0075)	(0.0075)
Cumulative Homicides (log) * Lower-Quality		-0.0131***		-0.0133***		-0.0136***
		(0.0033)		(0.0032)		(0.0031)
Total Effect: Lower-Quality		-0.0182***		-0.0173***		-0.020***
Property and Locality Characteristics	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES
Bank Fixed Effects	YES	YES	YES	YES	YES	YES
Appraiser Fixed Effects	YES	YES	YES	YES	YES	YES
Municipality Fixed Effects	YES	YES	YES	YES	YES	YES
Municipality Trends	NO	NO	NO	NO	NO	NO
Interaction: Month Effect * Lower-Income	NO	YES	NO	YES	NO	YES
Observations	1,370,767	1,370,767	1,370,767	1,370,767	1,370,767	1,370,767
R-Squared	0.924	0. 924	0. 924	0. 924	0. 924	0. 924

Clustered standard errors in parentheses (municipality).
*** p<0.01, ** p<0.05, *p<0.1

7. The Effect of Persistent Violence

Besley and Mueller (2012) argue that violence affects housing prices and that homicides are an observable proxy for violence. The distinction turns out to be important: patterns of homicide that lead to more violence in the future affect housing prices more than short-lived increases in violence. We now test this prediction using a reduced form model, taking advantage of the fact that the duration of the violence varied widely across municipalities.

We use four different definitions of persistent violence that reflect the magnitude of the increase seen in 2008-2011, as well as the changes in the level of violence witnessed in the interim years. To be considered "persistent," the pattern of homicides must fulfill two conditions: i) the increase in crime must have been at least 150 percent (or 200 percent) from 2008 to 2011;

and ii) each year, the crime rate must have been higher than it was the previous year *or*, at the very least, there must have been more homicides than there were in the base year (2008). Depending on the definition, there are about 270 municipalities that are classified as experiencing a "persistent" increase in violence.

We modify the specification for equation (3) to include interactions with a "persistent" increase in DRHs. Thus, we estimate the following empirical models (5) and (6):

$$\log(P_{ijt}) = \alpha_t + \gamma_j + t\gamma_j + \emptyset PermanentIncrease_{ijt} + \alpha_t PermanentIncrease_{ijt} + \delta X_{ijt} + \beta \log(Cum.Hom.s_{jt}) + \theta PermanentIncrease_{ijt} \log(Cum.Hom._{jt}) + \varepsilon_{ijt} \quad (5)$$

$$\log(P_{ijt}) = \alpha_t + \gamma_j + t\gamma_j + \emptyset LowQuality_{ijt} + \alpha_t LowQuality_{ijt} + \delta X_{ijt} + \beta \log(Cum.Hom.s_{jt}) + \theta LowQuality_{ijt} \log(Cum.Hom._{jt}) + \vartheta PermanentIncrease_j \log(Cum.Hom._{jt}) + \rho PermanentIncrease_j LowQuality_{ijt} \log(Cum.Hom._{jt}) + \varepsilon_{ijt} \quad (6)$$

Table 12 shows the effect of persistent violence on housing prices. Columns (1) and (3) indicate the presence of persistent violence if the homicide rate rose by at least 150 percent (200 percent for the other columns) between 2008 and 2011 and if the homicide count climbed every year or, at the very least, relative to its 2008 level. Our main results hold true: there is no average effect of either short-lived or persistent increases in crime. These effects appear only in relation to the dwellings of the poorer segments of the population. As conjectured, the negative effects on prices for lower-income housing are about 28 percent—45 percent larger in situations where the increase in DRHs is persistent than they are in cases where the increase is short-lived.

Table 12. The Effect of Homicides on Housing Prices: Persistent vs. Short-Lived Increases in Homicides Log (Property Price)

	(1)	(2)	(3)	(4)
	Cumulative Homicides 6 months	**Cumulative Homicides 6 months**	**Cumulative Homicides 6 months**	**Cumulative Homicides 6 months**
Cumulative Homicide Rates (log)	-0.0003	-0.0013	0.0010	0.0000
	(0.0026)	(0.0026)	(0.0028)	(0.003)
Cumulative Homicides (log) x Persistent Increases	-0.0014	0.0010	-0.0019	0.0006
	(0.0037)	(0.0038)	(0.0039)	(0.0039)
Cumulative Homicides (log) x Lower-Quality			-0.0120***	-0.0120***
			(0.0035)	(0.0034)
Cumulative Homicides (log) x Lower–Quality x Persistent Increases			-0.0029	-0.0038
			(0.0029)	(0.0033)
Total Effect: Persistent Increases	-0.0016	-0.0003		
Total Effect: Short-Lived Increases – Lower-Quality			-0.0110***	-0.0120***
Total Effect: Persistent Increases - Lower-Quality			-0.0150***	-0.0150***
Total Effect: Short-Lived Increases - Higher-Quality			0.0011	0.0000
Total Effect: Persistent Increases– Higher-Quality			-0.0008	0.0006
Property and Locality Characteristics	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES
Bank Fixed Effects	YES	YES	YES	YES
Appraiser Fixed Effects	YES	YES	YES	YES
Municipality Fixed Effects	YES	YES	YES	YES
Municipality Trends	YES	YES	YES	YES
Interaction: Month Effect * Lower-Quality	NO	NO	YES	YES
Observations	1,370,767	1,370,767	1,370,767	1,370,767
R-Squared	0.93	0.93	0.93	0.93

Clustered standard errors in parentheses (municipality).
*** p<0.01, ** p<0.05, *p<0.1

Note: As in the previous section, to show that our results do not depend heavily on the fact that we exclude the houses without geo-localization data from our original database, we ran the regression for equations (5) and (6) with the entire database (and, thus, without controlling for locality size). Table 13 in the Appendix shows the effect of persistent violence on housing prices. Columns (1) and (3) indicate the presence of persistent violence if the homicide rate rose by at least 150 percent (200 percent for the other columns) between 2008 and 2011 and if the homicide count climbed every year or, at the very least, relative to its 2008 level. Our main results remain unchanged: there is no average effect of either short-lived or persistent increases in crime. These effects appear only in relation to the dwellings of the poorer segments of the population. When using the whole database, the effect of temporal crime has no effect on either the lower-income or higher-income houses. However, the impact of the permanent increase in crime has 0 effect on higher-income houses but a negative and highly significant effect on

lower-income ones. As conjectured, the negative effects on prices for lower-income housing are about 100 percent—150 percent larger in situations where the increase in DRHs is persistent than where the increase is short-lived. This, again, suggests that crime affects significantly the prices of lower-income houses when it is permanent, whereas the higher-income houses do not seem to be affected by permanent or short-lived increases in crime. Definitions of "persistent increases:" Model (1) and (3): (Increase in homicides > 150 percent between 2011 and 2008) AND (homicides in every year >= homicides in the previous year OR homicides in every year > homicides in 2008).

8. Conclusion

Crime is a serious social phenomenon that affects the population's welfare in many ways. Although it is much more prevalent in less-developed countries than in developed ones, it has been woefully understudied in the latter. In Mexico, crime has increased sharply in recent years. In fact, since 2008, more than 50,000 Mexicans have been killed—a really high number, compared to the number of deaths occurring in other recent conflicts, such as the campaigns waged by the Irish Republican Army (3,500) or ETA (1,000) in Spain. Although the government and the private sector are both claiming that this violence is hurting the Mexican economy badly, no rigorous study has been undertaken to support this claim.

We focus on the effect of crime on home prices, which reflects people's willingness to live in a certain area, by computing the (negative) value of the dis-amenities of a location. Taking advantage of the unpredictable nature of drug-related homicides in Mexico, we exploit within-municipality variation over time and an extensive database on housing prices and characteristics at the national level. We first show that crimes tended to appear as "shocks" (or deviations from trend) and, thus, were not related to economic variables. Second, we show that crime has in fact triggered a substantial reduction in housing prices, which is concentrated exclusively in poor areas: one standard deviation in crime causes about a 3-4 percent decline in the price of poor people's houses and generates no decrease in the non-poor ones. Given that a home is one of the most important assets that families own, this decline represents a substantial loss of wealth, especially among the poor. Crime thus has a regressive redistributive effect.

Finally, we also find that, where violence has been persistent (i.e., where there has been a large, sustained increase in homicides), the negative effects on housing prices in poor areas are 40 percent greater than they have been in areas experiencing short-lived spikes in DRHs. The findings described in this paper are in line with those of Di Tella et al. (2010), studying another environment and type of conflict, who also find that violence places a heavy burden on the poor,

and with Besley and Mueller (2012), who find that peace leads to a significant increase in housing prices, with the effect being stronger in those regions where the violence was greatest.

A plausible interpretation of our results is that DHR affects the amenities of the poor disproportionately more in the municipalities that were shocked by that type of violence. Consistent with this idea, poor households tend to move more than non-poor households, and prices of poor people's houses tend to decrease in those municipalities as a function of the intensity of the crime shock. We present evidence suggesting that, indeed, crime has a big differential effect for the poor in terms of their perception of security. We also show that, although poor and non-poor households tend to move more in municipalities where crime grew the most, the effect is more than 50 percent larger in the case of poor households. Altogether, the empirical evidence is consistent with our interpretation.

References

Abadie, A., and J. Gardeazabal. 2003. "The Economic Costs of Conflict: A Case Study of the Basque Country." *American Economic Review* 93(1): 113-32.

Astrogyan, L., and D. Shirk. 2011. "Drug Trafficking Organizations and Counter-Drug Strategies in the U.S.-Mexican Context." In: A. Selee and D. Shirk, editors. *Shared Responsibility*. San Diego, United States: University of California at San Diego, Trans-Border Institute.

Bailey, J. 2011. "Combating Organized Crime and Drug Trafficking in Mexico: What Are Mexican and U.S. Strategies? Are They Working?" In: A. Selee and D. Shirk, editors. *Shared Responsibility*. San Diego, United States: University of California at San Diego, Trans-Border Institute.

Bailey, J., and R. Godson, editors. 2000. *Organized Crime and Democratic Governability: Mexico and the U.S.-Mexican Borderlands*. Pittsburgh, United States: University of Pittsburgh Press.

Besley, T., and H. Mueller. 2012. "Estimating the Peace Dividend: The Impact of Violence on Housing Prices in Northern Ireland." *American Economic Review* 101(2): 810-33.

Castillo, J., D. Mejía, and P. Restrepo. 2012. "Illegal Drug Markets and Violence in Mexico: The Causes beyond Calderón." Bogota, Colombia: Universidad de los Andes. Mimeographed document.

Díaz-Cayeros, A. et al. 2011. "Living in Fear: Mapping the Social Embeddedness of Drug Gangs and Violence in Mexico." San Diego, United States: University of California, San Diego, Center for U.S.-Mexican Studies. Available at: http://irps.ucsd.edu/assets/001/502978.pdf

Dell, M. 2011. "Trafficking Networks and the Mexican Drug War." Cambridge, United States: Harvard University. Available at http://scholar.harvard.edu/files/dell/files/121113draft_0.pdf

Di Tella, R., S. Galiani and E. Schargrodsky. 2010. "Crime Distribution and Victim Behavior during a Crime Wave." In: R. Di Tella, S. Edwards and E. Schargrodsky, editors. *The Economics of Crime: Lessons from Latin America*. Cambridge, United States: National Bureau of Economic Research.

Escalante Gonzalbo, F. 2011. "Homicidios 2008-2009: La Muerte Tiene Permiso." *Nexos en Línea*. Accessed December 14, 2013. http://www.nexos.com.mx.

Kahn, M., and P. Bajari. 2005. “Estimating Housing Demand with an Application with Expanding Racial Segregation in Cities.” *Journal of Business & Economic Statistics* 23: 20-33.

Gibbons, S. 2004. “The Costs of Urban Property Crime.” *Economic Journal* 114(499):F441-F463.

Guerrero, E. 2009. *Nexos en Línea*. Accessed November 1, 2012. http://www.nexos.com.mx.

Guerrero-Gutiérrez, E. 2011. “Security, Drugs and Violence in Mexico: A Survey.” 7th North American Forum (October 6-8, 2011), Washington, DC, United States

Linden, L., and J. Rockoff. 2008. “Estimates of the Impact of Crime Risk on Property Values from Megan’s Laws.” *American Economic Review* 98(3): 1103-27.

Levitt, L., and S. Venkatesh. 2000. “An Economic Analysis of a Drug-Selling Gang’s Finances.” *Quarterly Journal of Economics* 115(3): 755-89.

Levitt, S. 2004. “Understanding Why Crime Fell in the 1990s: Four Factors that Explain the Decline and Six that Do Not.” *Journal of Economic Perspectives* 18(1): 163-90.

Molzahn, C., V. Ríos, and A. D. Shirk. 2012. “Drug Violence in Mexico: Data and Analysis through 2011.” *Special Report for the Trans-Border Institute.* San Diego, United States: University of California at San Diego.

Rios, V. 2011. “Violencia Mediática.” *Nexos en Línea*. Accessed October 31, 2012. http://www.nexos.com.mx.

----. 2012. “Why Did Mexico Become So Violent? A Self-Reinforcing Violent Equilibrium Caused by Competition and Enforcement.” *Trends in Organized Crime.* New York, United States: Springer.

Snyder, R., and A. Durán-Martínez. 2009. “Does Illegality Breed Violence? Drug Trafficking and State-Sponsored Protection Rackets.” *Crime, Law and Social Change* 52: 253-73.

United Nations Office on Drugs and Crime. 2011. *World Drug Report*. New York, United States: United Nations.

Appendix

Table 13. The Effect of Homicides on Housing Prices: Persistent vs. Short-Lived Increases in Homicides (Robustness) Log (Property Price)

	(1) Cumulative Homicides 6 months	(2) Cumulative Homicides 6 months	(3) Cumulative Homicides 6 months	(4) Cumulative Homicides 6 months
Cumulative Homicides (log)	0.0018	-0.0013	0.0028	0.0032
	(0.0026)	(0.0026)	(0.0028)	(0.0032)
Cumulative Homicides (log) x Persistent Increases	-0.0042	0.0009	-0.0047	-0.0047
	(0.0039)	(0.0038)	(0.0040)	(0.0039)
Cumulative Homicides (log) x Lower-Quality			-0.0094*	-0.0092**
			(0.0048)	(0.0046)
Cumulative Homicides (log) x Lower-Quality x Permanente Growth			-0.0016	-0.0037
			(0.0035)	(0.0035)
Total Effect: Persistent Increases	-0.0025	-0.0004		
Total Effect: Temporal Growth - Lower-Quality			-0.0066	-0.0060
Total Effect: Persistent Increases - Lower-Quality			-0.0130***	-0.0150***
Total Effect: Temporal Growth - Higher-Quality			0.0028	0.0032
Total Effect: Persistent Increases - Higher-Quality			-0.0019	-0.0015
Property and locality characteristics	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES
Bank Fixed Effects	YES	YES	YES	YES
Appraiser Fixed Effects	YES	YES	YES	YES
Municipality Fixed Effects	YES	YES	YES	YES
Municipality Trends	YES	YES	YES	YES
Interaction: Month Effect * Lower-Quality	NO	NO	YES	YES
Observations	2,279,492	2,279,493	2,279,494	2,279,495
R-Squared	0.918	0.919	0.919	0.919

Clustered Standard Errors in Parentheses (municipality)

*** p<0.01, ** p<0.05, *p<0.1

Model (1) and (3): (Increase in homicides > 150% between 2011 and 2008) AND (homicides in every year >= homicides in the previous year OR homicides in every year > homicides in 2008)

Model (2) and (4): (Increase in homicides > 200% between 2011 and 2008) AND (homicides in every year >= homicides in the previous year OR homicides in every year > homicides in 2008)