The Impact of Violence in Mexico on Education and Labor Outcomes: Do Conditional Cash Transfers Have a Mitigating Effect?

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Abstract

This research explores the potential mitigating effect of Mexico's conditional cash transfer program, *Oportunidades*, on the education and labor impacts of increased homicide rates. Drug-related violence in Mexico has increased substantially since 2006, when former Mexican President Felipe Calderón initiated a crackdown on drug cartels. The increase in violence has been shown to have a negative impact on years of education and completion of compulsory schooling for young adults. In this study, panel data models are combined with a difference-in-differences approach to compare children and young adults who receive cash transfers with those who do not. Results are very sensitive to specification, but *Oportunidades* participation is shown to be positively associated with educational attainment regardless of homicide increases. Homicides are associated with decreases in likelihood of school enrollment and compulsory education completion; however, they also correspond with increases in educational attainment, with a larger effect for *Oportunidades* non-recipients. Despite many limitations, this study affirms the strategy of municipality-level fixed effects, considers many factors related to crime and victimization, and provides a novel examination of the relationship between drug violence and conditional cash transfers.

JEL classification: C23; D15; I20; I38; J24
Keywords: Conditional Cash Transfers; Education; Labor; Violence; Mexican Drug War

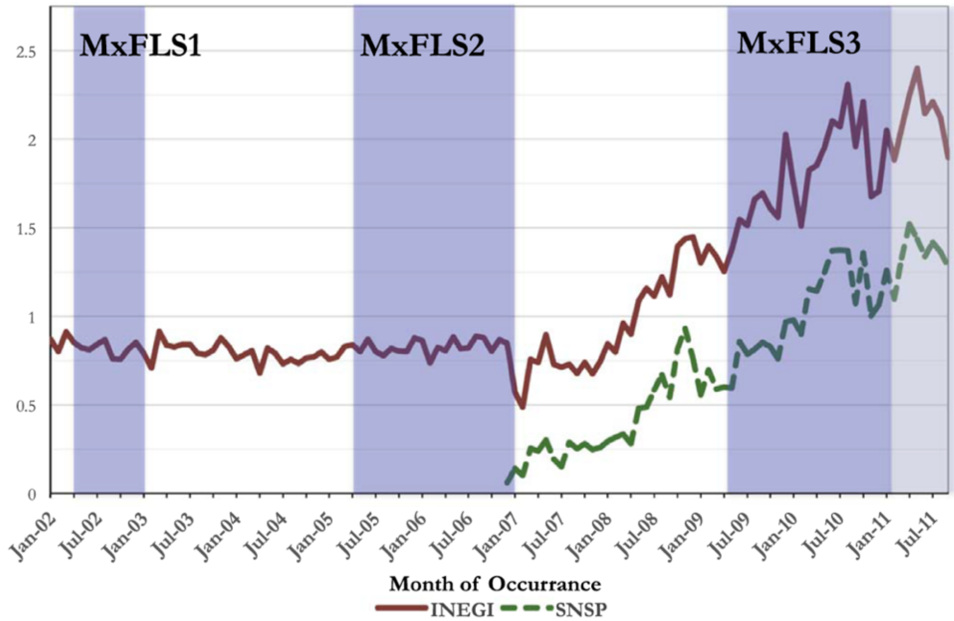
Introduction

Drug-related violence in Mexico has increased substantially since 2006, when former Mexican President Felipe Calderón initiated a crackdown on drug cartels. Although the crackdown was intended to reduce drug cartel activity, it actually resulted in a sharp increase in violent crime perpetrated by cartel members against each other and against government forces. This increase in local violence has been shown to have a negative impact on years of education and completion of compulsory schooling for young adults. Could any programs or methods help mitigate the impact of the violence?

One program that has been shown to have a positive impact on measures of human capital accumulation, including educational enrollment and attainment, is Mexico's conditional cash transfer program, *Oportunidades*. Conditional cash transfer programs (CCTs) like *Oportunidades* aim to reduce poverty by providing cash benefits to poor households conditional on behaviors such as mandatory health clinic visits and school enrollment. Studies in other settings have shown that conditional cash transfer programs can reduce the effects of other types of violence, including intimate partner violence (i.e. Buller et al., 2018), but to my knowledge, no study has observed the interactions between the effects of Mexico's drug-related crime increase and the impact of *Oportunidades.* This research explores the potential mitigating effect of *Oportunidades* on the education and labor impacts of increased homicide rates by using fixed effects and random effects models with interaction terms to compare children and young adults who receive cash transfers with those who do not.

Analyzing education and labor variables before and after 2006 provides a snapshot of the effects of a relatively exogenous and unanticipated increase in violence, as homicide numbers in Mexico increased sharply following Calderón's crackdown. Experts reported 121,669 homicides under Calderón's presidency from 2006 to 2012, an average of more than 55 people per day. This was in stark contrast to the terms of his two predecessors, which both saw significant declines in the homicide rate (Calderón, Rodríguez Ferreira & Shirk, 2018). Recent tallies suggest that one third to one half of all homicides in Mexico are related to organized crime-style violence and drug trafficking. Increased violence during this time period has been shown to be distributed geographically in a way that is not correlated with previous demographic and economic trends, allowing less biased estimate of the impact on household behaviors (Brown, 2016; Velásquez, 2015).

Fig. 1. Three Mexican Family Life Survey panels (MxFLS1, 2 and 3) overlaid with Mexico's monthly homicide rate per 100,000 population. The INEGI data (solid line) represent all recorded homicides in Mexico, and the SNSP data (dashed line) reflect homicides attributed specifically to drug-related violence and the crackdown on cartels. Most of the overall increase in violence can be attributed to the drug-related violence.



Source: INEGI and SIMBAD municipal and state homicide data, from Brown and Velásquez (2017).

Previous studies of Mexico's drug violence spike and human capital find that children exposed to local violence, especially males, experience lower levels of education, exhibit lower cognitive ability, and are more likely to work, while increased violence also negatively impacts salaries and other labor market outcomes for adults (Brown and Velásquez, 2017; Kato Vidal, 2015; Velásquez, 2018). The most frequently cited mechanisms for these effects are fear of victimization or financial as household budgets are restricted. Some studies also consider supply-side variables with regard to schooling availability, but the spike in Mexico's drug-related violence did not have a large effect on infrastructure, so this is less likely to be the main cause behind the change in outcomes (Brown and Velásquez, 2017). Other research finds that Mexico's conditional cash transfer program has opposite effects on education and labor outcomes. Thus, participation in conditional cash transfer programs may have a mitigating effect on the negative impacts of drug-related violence, especially if the underlying mechanism is financial and *Oportunidades* can help offset the cost.

Conditional cash transfers (CCTs) are targeted payments that aim to reduce poverty by providing flexible cash resources to poor families and requiring compliance with certain conditions such as mandatory school attendance of children, regular check-ups, and participation in nutrition training programs. Since the late 1990s, conditional cash transfer programs have become a widespread approach to poverty alleviation in Latin America. The first CCTs in Latin America were pioneered in Mexico and Brazil in the late 1990s, but spread to 18 countries and covered 129 million beneficiaries in the region by 2011 (Stampini & Tornarolli, 2012).

Mexico's CCT program, *Oportunidades*, was first established by the state in 1997 in certain rural areas with target poverty rates (Skoufias, Davis, & de la Vega, 2001).[2] By 2007, *Oportunidades* provided benefits to over 5 million families in every county in the country, to roughly 18% of Mexico's entire population (Fiszbein, Schady, & Ferreira, 2009). Poverty in Mexico is widespread, with over 52 million out of 112.6 million Mexicans in 2010 living with at least one social insufficiency and income not high enough to satisfy their basic needs. The percentage of *Oportunidades* beneficiary families varies greatly by state—in some states with the lowest indices of human development, more than half of the population receives *Oportunidades* benefits. Funding for *Oportunidades* comes from the Federal Government, with this program warranting the highest budget granted to any program. By 2006, its budget increased to 33 thousand million pesos (Programa de Desarrollo Humano Oportunidades, 2012).

Participating households receive grants every two months for each child under the age of 22 enrolled between the third grade of primary school and the final grade of high school. These grants increase in value for each grade and are 10 to 15 percent higher for female children starting in secondary school to further incentivize the education of girls. There is an additional incentive for students who graduate from high school before turning 22 years old. This study focuses on individuals ages 8-21 to restrict the sample to those potentially eligible for the *Oportunidades* education scholarship. *Oportunidades* also provides basic health care and nutritional stipends to all family members (Bailey et al., 2007; Parker, 2003). In 2004, households received an average of US$31 per month in benefits, disbursed every two months to a woman in the family, usually the mother (Bailey et al., 2007; Levy, 2006). Estimates suggest

2. *Oportunidades* was called *Progresa* until 2001, when it was renamed and expanded to include urban households. Since 2014, it has been called *Prospera* (Covarrubias, 2018). For the purposes of this study, this program will be referred to as *Oportunidades*, as this was the name in use at the time the survey data were collected.

that program income accounts for about 25% of total resources in *Oportunidades*-receiving households: a clear financial incentive to comply with conditionalities (Farfán, Genoni, Rubalcava, Teruel, & Thomas, 2012).

Many studies have demonstrated the positive effects of *Oportunidades* and other CCT programs on factors such as educational attainment, health outcomes, consumption, and reduced poverty (Fiszbein, Schady, & Ferreira, 2009; Parker, 2003). One 2004 study found that, in rural areas, school dropouts of teenagers between 16 and 19 years old decreased 23% with *Oportunidades* (Programa de Desarrollo Humano Oportunidades, 2012). Despite these advances, only 62% of students in Mexico reached secondary school (grade 7) as of 2011 and only a quarter reached college or university (Rama & Boadle, 2011). Education decisions are particularly important for young adults ages 14-17, as until 2013, compulsory education extended up to completion of ninth grade, or the end of secondary school. This stage is typically reached by students around the age of 14 or 15. In 2013, this requirement was extended to also include high school or "preparatoria," although many students still do not fulfill this requirement (Magaziner & Monroy, 2016). The impact of programs such as *Oportunidades* is critical to encourage the development of human capital and achieve long-term poverty reduction goals, and it would be devastating if increased violence lessened their impact.

Because of conditionalities, part of the impact of CCTs can be attributed to increased utilization of resources such as payment points, schools, and health clinics, despite travel costs or potential risk. Until 2011, all *Oportunidades* benefits were paid directly to beneficiary households as cash or through direct deposit. These transactions could only take place at designated temporary payment points, TELECOMM telegraph offices, or the savings account branch (Dávila Lárraga, 2016). Increased violence associated with Mexico's drug war could be a barrier for families to access these payment points or other essential services for participation in the CCT program including schools and health clinics, especially if they live in a rural area and must travel some distance to reach these services. However, participation in *Oportunidades* may also provide incentives for families to continue making these trips despite fear, or provide enough financial incentive that young adults do not need to find work if household budgets are constrained as violence increases. While an increase in violence may lower educational outcomes, this research endeavors to discover if those receiving *Oportunidades* benefits experience different effects compared with those who do not participate in the program.

Literature Review

Key literature related to crime in Latin America and *Oportunidades* can be considered under the following categories: I. Current approaches to understanding crime, including some studies that have examined the impact of CCTs on crime reduction; II. Actual crime rates vs. a household's perception of risk, and how that relates to *Oportunidades*; and III. Other research on the mechanisms related both to *Oportunidades* and violence that affect education and labor. Understanding these three areas is critical to grasping the Mexican context of crime, education, and cash transfers.

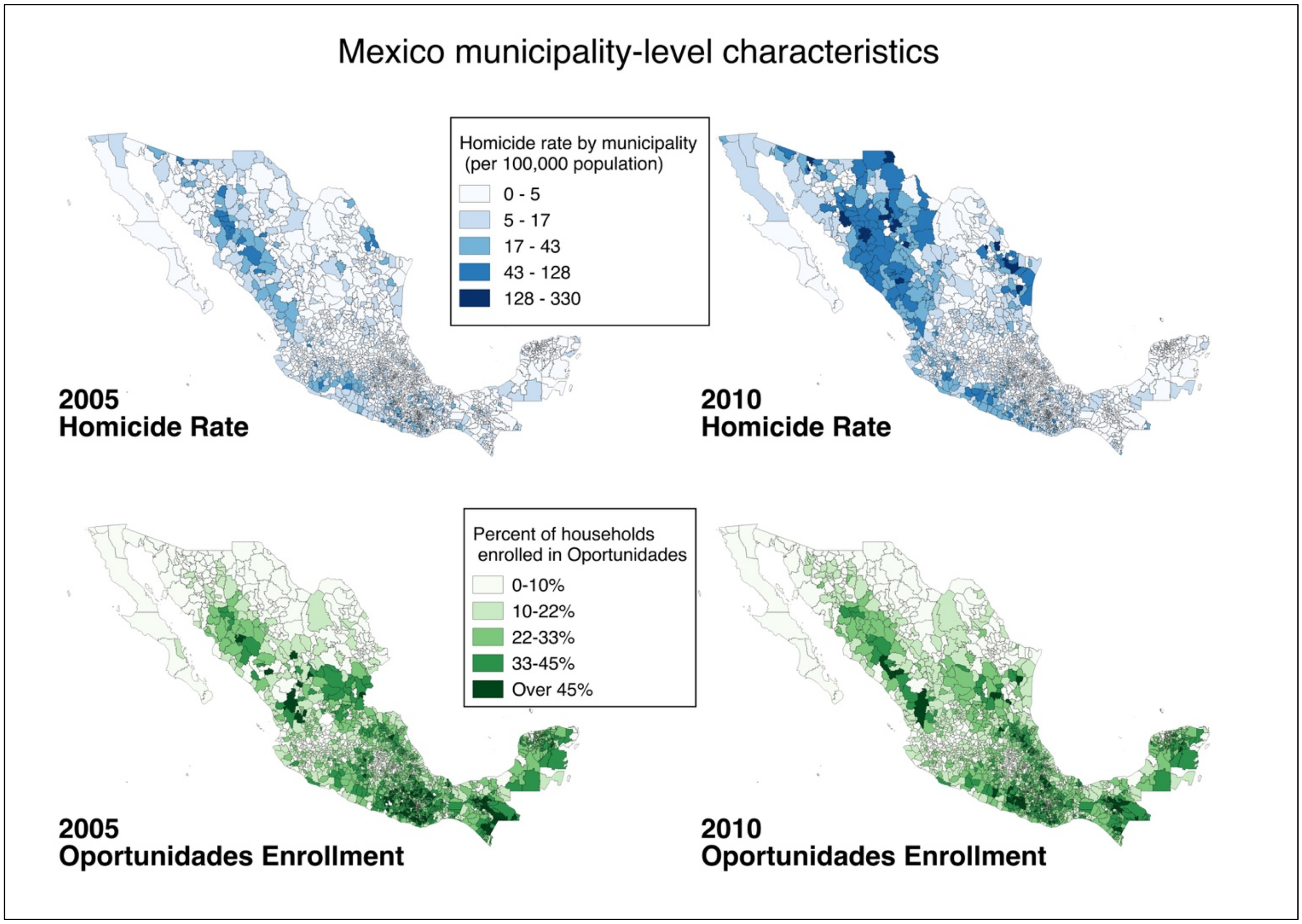
I. Current Approaches to Understanding Crime

Current approaches to examining crime in Latin America focus on the links between crime, inequality, and the role of social control and state services (Lance, 2014). The direct, positive relationship between inequality and high crime has been well-studied (Di Tella, Edwards & Schargrodsky, 2010). In these situations, crime can stem from low-income people attempting to improve their economic situation. Poverty and inequality are also related to the distribution of cash transfers, as these programs are generally targeted to poor households. To qualify, *Oportunidades* recipients must live below the poverty line, so these same violence-susceptible areas are also frequently those with high rates of participation in the CCT program. However, two studies of Mexico and Brazil found that the percentage of households in a municipality enrolled in CCT programs also had a significant causal effect on reducing the homicide rate in that area (Lance, 2014; Chioda, De Mello, & Soares, 2016). Regardless, the post-2006 spike in drug-related violence in Mexico offers an opportunity to analyze violence as a geographically exogenous shock, as the spike was not closely related to poverty rates or *Oportunidades* enrollment, but to drug trafficking routes and territories.

Social control can also affect the level of violence in an area. Social control encompasses internalization of societal norms and values as well as formal sanctions imposed by governments. There is evidence that government crackdowns can cause large and lasting increases in the homicide rate through fragmentation and increased violence along new, alternative trade routes (Dell, 2015). Policy change and government action is widely accepted as the driving force behind the rapid increase in violence in Mexico after 2006 (Brown & Velásquez, 2017). Former President Calderón's military strategy involved increasing direct confrontations with leaders of

Mexico's Organized Crime Groups (OCGs) through direct killing or capture. This strategy resulted in fragmentation of cartels, a growing power struggle within and between OCGs, expansion to new geographic areas, and displays of violence to establish territorial control.

Fig. 2. The homicide rate and household *Oportunidades* enrollment rate by municipality, 2005 and 2010. The homicide rate increased substantially in certain municipalities, primarily along drug trafficking routes, while *Oportunidades* enrollment rates remained more constant.



Source: INEGI homicide data and SIMBAD state and municipal population data. Map visualizations created in QGIS.

II. Crime Rates and Perception of Risk

As violence increases, a household's perception of the risk of violence also changes, potentially influencing their compliance with *Oportunidades* requirements, as they must travel to payment points, schools, and health clinics. Many factors may affect perception of risk, including social linkages within communities and demographic characteristics, besides the actual homicide rate itself. In a study of Brazilian neighborhoods, Villarreal and Silva find that lower-income neighborhoods have higher levels of social cohesion (2006). Rather than being associated with lower crime levels, this social cohesion is associated with a higher perceived risk of victimization relative to actual risk due to greater spread of information regarding crime. In the U.S., studies of urban areas also find residents' fear of crime to be only weakly related to actual crime risk (Skogan & Maxfield 1981; Taylor & Hale 1986). This stems from residents associating risk not only with their direct experiences, but also with others' experiences, which can cause an especially large effect in areas with high social cohesion.

Increased violence and perception of risk could have a significant impact on household participation in CCT programs. One study of Pakistan found that exposure to violent conflict reduced household access to government-run cash transfer programs, although it had no effect on non-state transfers from NGOs and private aid organizations (Ghorpade, 2018). In this case, militant groups seemed to contest state-related involvement specifically. Although cartels and other perpetrators of violence in Mexico have not been shown to oppose *Oportunidades* distribution, increased violence may still reduce ability to distribute, receive, or qualify for benefits. Brown, Montalva, Thomas, and Velásquez (2014) show that insecurity and uncertainty brought on by the increase in drug-related violence in Mexico leads to a widespread increase in risk aversion. This could affect families' decisions to travel to payment sites and collect benefits, especially when the level of violence and risk increases.

III. Other Research on Mechanisms Related to Oportunidades and Violence

The effect of violence on Mexico's *Oportunidades* has not previously been studied in depth. However, related work reveals trends from violence that may be related to participation in conditional cash transfer programs. An increase in crime may negatively impact salaries and other labor market outcomes (Kato Vidal, 2015; Velásquez, 2018), which could generate increased poverty and participation in *Oportunidades*. Separately, Brown and Velásquez (2017) estimate that children exposed to local violence experience lower levels of education and exhibit lower cognitive ability, and are more likely to work. This signals that children and young adults are leaving school earlier to join the workforce due to financial incentives. Another study from Márquez-Padilla, Pérez-Arce, and Rodríguez-Castelán (2015) finds that increased violence due to the "War on Drugs" in Mexico did not actually have a significant direct impact on the total number of students enrolled at schools in different municipalities. However, they were unable to follow individual students over time to determine which factors played into enrollment decisions at an individual level during periods of violence.

Negative impacts of the drug violence shock work in the opposite direction of many demonstrated effects of *Oportunidades*, which include enhanced welfare in school attendance, income, nutrition, and health (Debowicz & Golan, 2013). As school enrollment is a requirement to receive benefits, violence could affect CCT-receiving and non-receiving families differently as *Oportunidades* creates incentives for families to keep children in school longer. *Oportunidades* is effective because it involves both a direct, financial effect in the form of increased income and also requires behavior such as school attendance. Whether the impacts of drug violence are related to financial constraints or fear of victimization, the multi-pronged approach of *Oportunidades* may help it act as a mitigator.

Another factor that may be related both to perceptions of violence and to *Oportunidades* participation is selective migration. This may introduce bias if *Oportunidades* participants migrate differently than non-participants, but the literature on *Oportunidades* and migration patterns is mixed. One study shows that households receiving *Oportunidades* are more likely to migrate internationally, but the impact on domestic migration is less clear (Ishikawa, 2014). Another finds that conditional transfers may increase domestic migration for some households, while decreasing it for others, due to competing income factors (Angelucci, 2011). This effect, along with other potential endogeneity between *Oportunidades* and homicide rates, is considered in the Empirical Specification, section II.

Data

The effects of increased violence on CCT and non-CCT participants are analyzed using panel data from the Mexican Family Life Survey and monthly homicide data from the Instituto Nacional de Estadística y Geografía (INEGI). These datasets are combined to explore changes in household and individual outcomes relative to homicide rates. Correlations between independent variables, which are quite low overall, are discussed in Appendix B.

I. Mexican Family Life Survey Data

The Mexican Family Life Survey (MxFLS) is a longitudinal study representative of the Mexican population at both the national and regional levels. The survey includes information on income and assets, consumption, perception of violence, education, migration, health, well-being, and habits for all members of a household. The data were collected in three waves over a ten-year time period: 2002, 2005-2006, and 2009-2012. The first panel in 2002 included a sample of about 8,400 households (35,000 individuals) in 150 rural and urban communities randomized by demographic variables to create a nationally representative sample. These same participants were re-interviewed for the second and third panels, including individuals who migrated, with a 90% re-interview success rate. The 2005-2006 and 2009-2012 panels can be used to study the same individuals before and after the spike in violence, making this dataset an incredibly useful tool to analyze changes in behavior related to the War on Drugs.

Due to confidentiality, household variables for *Oportunidades* participation are excluded from publicly available MxFLS datasets and household participation must be inferred from individual scholarship participation for children under 15. In this study, household participation in *Oportunidades* during a given survey period is marked positive if one or more children under 15 in that household were enrolled in the program at the time of survey. Generating a household participation variable allows expansion of this study to individuals older than 14 if they have a younger sibling with *Oportunidades* participation information. These pools form the primary treatment and control groups.

Individuals are included in the study if they are at least age 8 at the time of the 2005-2006 panel and less than 22 at the time of the 2009-2012 panel. This captures all individuals who could be eligible for the *Oportunidades* education scholarship in both periods, as eligibility starts in the third grade of primary school, usually reached at age 8, and ends when the participant graduates from high school up until age 22. Slightly older individuals are used for the analysis of completion of compulsory education and labor participation: ages 15-16 and ages 14-17, respectively, as of the MxFLS3 (2009-2012) panel, as these groups are at a critical period for education and labor decisions. Until 2013, compulsory education extended up to completion of ninth grade, which generally occurs around the age of 14 or 15.

Table 1A. Observations by gender for 8-21 age group with complete MxFLS observations for necessary variables (Mexican Family Life Survey).

	2005-2006 survey panel	**2009-2012 survey panel**
Total observations	4,490	4,490
Female	2,223 (49.51%)	2,222 (49.49%)
Male	2,267 (50.49%)	2,268 (50.51%)

Table 1B. Key summary statistics for 8-21 age group with complete MxFLS observations for necessary variables (Mexican Family Life Survey).

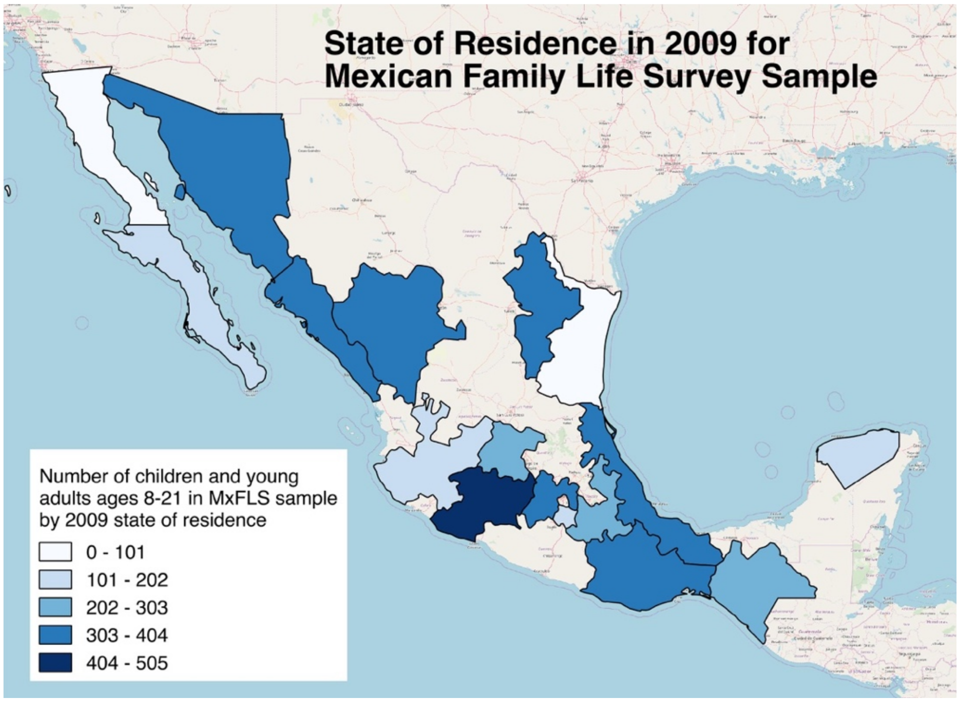
	2005-2006 survey panel				**2009-2012 survey panel**			
	Mean	*Std. Dev.*	*Min*	*Max*	*Mean*	*Std. Dev.*	*Min*	*Max*
Age	12.23	2.55	8	20	16.54	2.57	9	21
Current school enrollment	0.88	0.33	0	1	0.58	0.49	0	1
Years of education	5.74	2.63	0	16	9.01	2.81	0	16
Percent of possible years of education completed	0.94	0.18	0	1	0.87	0.21	0	1
Completion of compulsory education	0.15	0.35	0	1	0.59	0.49	0	1
Labor participation	0.04	0.20	0	1	0.19	0.39	0	1

Table 1C. *Oportunidades* participation data for 8-21 age group with complete MxFLS observations for necessary variables (Mexican Family Life Survey).

Survey panel	**Individuals in participating households**	**Individuals not in participating household**
2002	1,338 (28.80%)	3,152 (70.20%)
2005-2006	1,778 (39.60%)	2,712 (60.40%)
2009-2012[3]	1,232 (40.29%)	1,826 (59.71%)

3. Data for 2009-2012 *Oportunidades* participation is not required to be included in the sample, as the effects of participation are examined based on the prior panel. Thus, there are fewer observations here, but it is still interesting to see.

Fig. 3. Map of state residency for 8-21 age group with complete MxFLS2 and MxFLS3 observations.



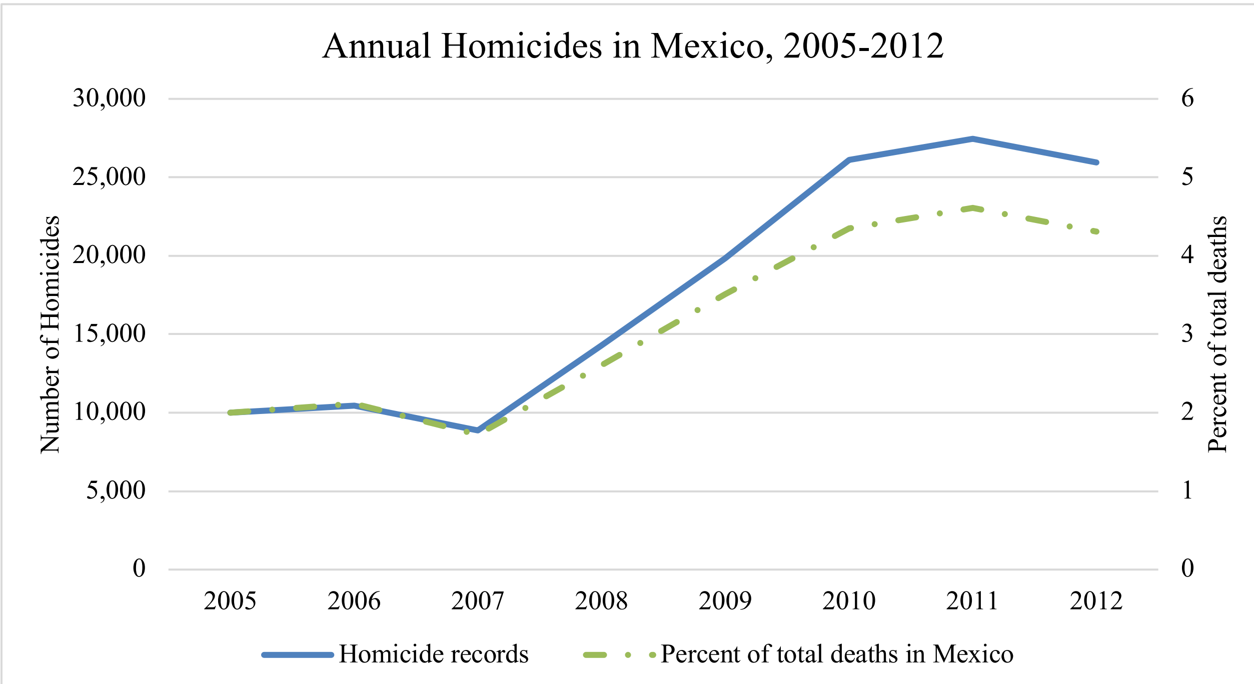
Source: Mexican Family Life Survey. Map visualization created in QGIS.

Fig. 3 displays the geographic distribution of individuals in the sample dataset—clearly, not all states are represented. Perhaps most notably, there are no observations from the northern state of Chihuahua, which includes the city of Juárez. Cities along the border between Mexico and the United States are known as particular centers of drug violence, as also shown in Fig. 2. This data limitation may mean that the variation in the homicide rate in not as extreme in the sample, which could adversely impact the ability to identify significant effects.

II. INEGI Homicide Data

In addition to data from the Mexican Family Life Survey, INEGI data are used to track monthly homicide rates by municipality. INEGI is a public, autonomous, national organization that delivers a wide variety of information about Mexico. Mortality data are publicly available from 1990-2017 and include microdata for all general deaths in Mexico. Records for 2000-2017 were filtered for homicides to calculate a homicide rate for each municipality by month and year that was merged with Mexican Family Life Survey responses, based on the municipality of residence of the surveyed household and the date of the survey. The homicide rate is a commonly-used variable for studying crime and violence in general, as it is not subjective and the stark nature of the crime makes it less liable to misreporting.

Fig. 4. INEGI national homicides in Mexico by date occurred, 2005-2012.



In 2005, the overall mean homicide rate for municipalities with at least one homicide was 9.95 per 100,000 population, but by 2010 this average increased to 19.80 homicides per 100,000 people (Table 2). These data confirm that there was a large spike in homicides and violence during the intervening time period, and that the number of homicides varies greatly between municipalities.

Table 2. Municipality-level homicide rates in Mexico, 2005 and 2010 (INEGI).

Year	Number of municipalities with at least one homicide	Mean homicide rate (per 100,000 pop)	Standard deviation	Minimum	Maximum
2005	1,306	9.95	15.74	0.32	330.033
2010	1,421	19.80	52.96	0.43	1111.96

Homicide rates are calculated for each observation in the Mexican Family Life Survey by totaling the number of homicides in that municipality for the 12 months prior to survey and adjusting per 100,000 population.[4] Averages for the individuals in the dataset used for this study are presented below, which show that the average homicide rate more than doubled between the two panels. However, these average rates are much lower for both panels than Mexico overall, suggesting that this sample does not include many observations from municipalities with the highest homicide rates. As shown above in Fig. 3., key states near the border, including Chihuahua, have no observations in the sample filtered by age.

Table 3. Municipality-level homicide rates for MxFLS 8-21 age group (Mexican Family Life Survey).

Panel/year surveyed	Observations	Mean homicide rate (per 100,000 pop)	Std. Dev.	Min	Max	Mean quartic root of homicide rate
2005	3,897	3.70	4.24	0	34.15	1.08
2006	591	6.30	7.96	0	68.05	1.33
2007	2	3.18	0	3.18	3.18	1.34
MxFLS2 Total	4,490	4.05	4.97	0	68.05	1.11
2009	3,207	8.52	9.18	0	67.10	1.48
2010	1,156	10.83	13.76	0	73.90	1.53
2011	118	10.85	30.11	0	321.65	1.56
2012	9	2.31[5]	1.31	0.94	3.81	1.19
MxFLS3 Total	4,490	9.16	11.56	0	321.65	1.50

III. Crime and Victimization Data

As discussed in the literature review, perception of risk may or may not be closely correlated with actual homicide rates. If fear of victimization drives household behavior, it is important to examine measures for this directly. This fear might also be one mechanism behind

4. Municipality-level population estimates are only recorded by the Mexican Census every 5 years (in 2000, 2005 and 2010), so population estimates for intervening years were calculated using the average population growth percentage between the two nearest estimates.
5. The low average homicide rate for 2012 is due to the low sample size—all 9 complete observations from 2012 were from the states of Puebla or Yucatán, which did not experience as large a homicide rate increase as Mexico overall.

any observed difference between *Oportunidades* participants and non-participants, if *Oportunidades* encourages households to attend school despite increased risk. The MxFLS includes dozens of variables related to crime perception and victimization, including respondent observation of behaviors such as drug use, robberies, and gang violence in the neighborhood, questions about general feelings of safety, and personal experiences with friends and family members as victims of certain crimes. This multitude of variables makes it difficult to determine which are the most crucial indicators of a household's perception of crime risk to include in this analysis.

To account for this, principal component analysis (PCA) was conducted in Stata to determine key components and calculate indices related to crime risk perception. Principal component analysis is a statistical procedure that transforms a set of possibly correlated variables into a set of linearly uncorrelated variables called principal components that can help identify relationships between them. PCA was run on twenty-one household variables related to crime and victimization from the Mexican Family Life Survey, and the seven most significant components were identified and calculated. PCA weighting tables and significant components are included in Appendix A. Upon observation, the components do not appear to strongly identify effects related to groups of similar variables, so were withheld from the final analysis to aid interpretability of the results.

Instead, certain variables were selected to be included directly in the regression models. The selected victimization variables include those most likely to be relevant given Mexico's situation, specifically: whether gangs are frequently present in the neighborhood, whether the household head feels safe at home, and the number of times a family member or friend has been assaulted, robbed or kidnapped in the past 5 years. All victimization variables are reported by household respondents.

Table 4. Summary statistics of variables related to perception of crime and victimization for 8-21 age group (Mexican Family Life Survey).

Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
MxFLS2					
Gangs present	4,490	0.21	0.41	0	1
Feel safe at home	4,490	0.92	0.27	0	1
People in locality trustworthy	4,416	0.79	0.41	0	1

Number of personal crime incidents	4,490	0.38	1.71	0	33
MxFLS3					
Gangs present	4,490	0.25	0.43	0	1
Feel safe at home	4,490	0.91	0.28	0	1
People in locality trustworthy	4,418	0.79	0.41	0	1
Number of personal crime incidents	4,490	0.58	3.29	0	101

Theoretical Framework

The literature reveals that increased violence is associated with a decreasing or ambiguous effect on education outcomes for young adults. Conditional cash transfer programs like *Oportunidades* have been observed to work in the opposite direction, increasing educational attainment through financial incentives and conditionalities. Although no prior studies have focused on the interaction of these effects, it is possible that CCTs could be one policy that mitigates the impact of the violence. Because *Oportunidades* provides direct financial incentives for low-income families to send their children to school and to participate in regular clinic visits and trainings, young adults from these families may be less affected by pressures to withdraw from school to earn an income or to avoid crime risk. This theory would suggest a mitigating effect of *Oportunidades* on a given outcome for participating households compared to otherwise similar non-participating households. This analysis presents the effects on percent of possible years of educational attainment, current school enrollment, completion of compulsory education, and labor force participation for children and young adults.

Empirical Specification

I. Difference-in-Differences Approach

A difference-in-differences approach is used to identify the impact of the homicide rate on four outcome variables—educational attainment, current education enrollment, completion of compulsory education, and labor force participation—for children and young adults, along with the additional impact associated with participation in *Oportunidades*. A panel data model with individual fixed effects is used for estimation of educational attainment, while a random effects logit model is used for current education enrollment and labor force participation due to time invariance of the binary outcome variable for many individuals. Completion of compulsory education is modeled with a standard logit model as completion tends to occur at a specific age and does not lend itself to the use of panel data. The last three are all binary outcomes, so a logit or probit model is most appropriate to determine the probability that an observation with particular characteristics will fall into a specific category.

The panel dataset used for this analysis was constructed with two observations for each individual who fell in the specified age range during both the 2005-2006 panel and the 2009-2012 panel. Each observation includes demographic, education, and homicide rate information from that survey panel, as well as information on homicide rates and *Oportunidades* participation from the previous panel (the 2002 panel for 2005-2006 observations, and the 2005-2006 panel for 2009-2012 observations). This allows for calculation of the percent change in the homicide rate since the previous period. *Oportunidades* participation information is used from the prior panel rather than the current panel to control for endogeneity between *Oportunidades* enrollment and education outcomes in the same period, given that attending school is required to receive the scholarship. This variable thus represents the lagged effect of household participation in *Oportunidades*.

Both the individual fixed effects model and random effects logit model use an indicator variable for *Oportunidades* participation in the prior period, transformed measures of the current homicide rate and percent change in the homicide rate, and an interaction term between *Oportunidades* and the current homicide rate in that panel.

The fixed effects model for educational attainment is specified as follows:

$$(1)\; y_{ihjt} = \alpha_0 + \alpha_1(homrate)_{jt} + \alpha_2(percentchangehomrate)_{jt} + \alpha_3(oportunidades)_{h(t-1)} + \alpha_4\left(homrate_{jt} * oportunidades_{h(t-1)}\right) + \beta' X_{iht} + state_{ht} + year_{ht} + month_{ht} + \theta_i + \varepsilon_{ihjt}$$

In the above specification y_{ihjt} is the percentage of possible years of education for individual i, a member of household h, residing in municipality j at time t, where t is the period when they were surveyed. $homrate_{jt}$ is the quartic root of the homicide rate in the household's municipality in the twelve months prior to the survey date; $percentchangehomrate_{jt}$ is the percent change in the homicide rate since the previous panel; $oportunidades_{h(t-1)}$ is an indicator variable for whether someone in that individual's household received the *Oportunidades* scholarship at time $t-1$, i.e. in the previous panel; and $(homrate_{jt} * oportunidades_{h(t-1)})$ is the interaction term of the homicide rate and prior *Oportunidades* participation. [6]

X_{it} is a vector of time-varying household characteristics, including age, natural log of real income, [7] household size, whether the household lives in an urban or rural locality, [8] whether the household migrated between the two survey panels, and the variables related to victimization: gang presence in neighborhood, whether household head feels safe at home, and personal crime experience. The effect of increased violence may appear indirectly through these terms rather than through the direct homicide rate variables, if perception of victimization is the mechanism through which increased violence affects outcomes. Interaction terms between the homicide rate and various individual characteristics are also included in some models to see if the homicide rate has a different effect for different types of individuals. $state_{ht}$, $year_{ht}$ and $month_{ht}$ are dummy variables for the household's state of residence and the year and month in which the household was surveyed. For the fixed effects model, time invariant characteristics such as gender, parents' level of education, and whether the household is indigenous are absorbed into the individual fixed effect, θ_i . Fixed effects models are powerful because they control for variables, both observed and unobserved, that do not change over time for a given individual. Some models additionally include a municipality fixed effect (dummy variable) instead of a state fixed effect.

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6. The quartic root of the homicide rate is used to reflect diminishing marginal impact relative to an increasing homicide rate. i.e. an increase in the homicide rate from 19 to 20 per 100,000 population is likely to have less of an impact on a household's behavior or outcomes than an increase from 1 to 2. This is the same transformation applied by Brown and Velásquez (2017). The percent change in the homicide rate is recorded as 0 for municipalities with a homicide rate of 0 in both periods and 1 for households with a homicide rate of 0 in the first period and nonzero in the second period.
7. In all parts of this analysis, real income is calculated using historic inflation and consumer price index data for Mexico from Inflation.eu. Income is adjusted relative to 2013, the last survey year included in MxFLS3. The log transformation of real income is actually the log (real income + 1) to allow for the inclusion of households that report an income of 0.
8. An urban locality is defined here as any locality with population greater than or equal to 15,000, while a rural locality has a population under 15,000. This is consistent with a report on urban slums in Mexico (Connolly, 2003). Locality population data are included in the Mexican Family Life Survey.

The main coefficients of interest in model (1) are α_1, α_2, α_3, and α_4, which are estimates for the effect of the homicide rate, the effect of the change in the homicide rate, the effect of *Oportunidades* participation, and the interaction between *Oportunidades* and the homicide rate, respectively. The interaction term has the potential to reveal the additional impact of homicides on the outcomes of young adults in households participating in *Oportunidades*, compared with young adults from non-participating households. The effect of a 1-unit increase in the quartic homicide rate for non-participating households is α_1, while the effect for Oportunidades households is $\alpha_1 + \alpha_4$. If the coefficient α_4 on the interaction term is significant, it means that there is an additional impact, whether positive or negative, of the spike in violence on young adults from households participating in *Oportunidades* independent of the direct effect on educational attainment due to *Oportunidades*.

Alternatively, the random effects logit model for current school enrollment and labor force participation is the following:

$$(2)\ Logit(y_{ihjt}) = \alpha_0 + \alpha_1(homrate)_{jt} + \alpha_2(percentchangehomrate)_{jt} + \alpha_3(oportunidades)_{h(t-1)} + \alpha_4\left(homrate_{jt} * oportunidades_{h(t-1)}\right) + C'X_{iht} + state_{ht} + year_t + month_t + \varepsilon_{ihjt}$$

Most of the variables in model (2) are specified in the same way as model (1), but the vector of household characteristics $C'X_{iht}$ includes more variables that had to be excluded in the fixed effects model: gender, indigenous identity, and the years of educational attainment of the mother and father are now all included, in addition to the time-varying characteristics mentioned above. Education of parents is important when considering a child's education because these decisions are made largely by the parents, and there is evidence that they are influenced by their own experience (Eccles, 2005). [9]

Random effects are used in model (2) because an individual fixed effects logit model will drop all individuals for which the dependent variable does not change over time, which is frequent for a binary dependent variable. The random effects model assumes that individual and

9. While parents' educational attainment is an important control in this model, note that the model thus excludes all individuals for which one or both parental education variables are unavailable, including any single-parent households.

time effects are randomly determined and not correlated with included observed regressors and control variables. This allows for both cross-sectional comparison between individuals and time-series comparison for the same individual. This panel regression with random effects is used for current education enrollment and labor force participation, with respect to their age groups of interest.

A logit regression without random effects is used to model completion of compulsory education, using only data for individuals who were age 15-16 during the MxFLS3 panel. As no students in this age cohort had completed compulsory education at the time of MxFLS2, the full panel dataset is not used. Instead, a standard logit regression is run using only observations from MxFLS3 to facilitate cross-sectional comparison.

II. Threats to Identification: Accounting for Endogeneity Between Violence and *Oportunidades*

i. *Oportunidades* Participation Rates and the Spike in Homicides

The increase in violence in Mexico after 2006 is regarded as exogenous to many underlying demographic trends. However, it is still important to validate this claim with regard to *Oportunidades* enrollment rates specifically. Municipality-level homicide rate and *Oportunidades* enrollment percentages from the INEGI database are compared to see if there is a correlation between the percentage of households enrolled in *Oportunidades* in 2005 and the increase in the homicide rate from 2005 to 2010 in that municipality. The correlation is -0.1036, so the two are only weakly, negatively correlated. This negative correlation may be due to the fact that *Oportunidades* participation was generally lower in some of the border regions where crime increased the most, as seen in Fig. 2.

ii. Selective Migration

A household's decision to migrate could be based on levels of violence, as households might reasonably wish to move away from dangerous areas with high homicide rates. Additionally, the choice to migrate may be influenced by a household's participation in *Oportunidades*. Recipients of *Oportunidades* may be less likely to move because they want to maintain their benefits, or more likely to do so because they have more financial resources than otherwise similar families not receiving *Oportunidades*. As described in the literature review, past studies of the effects of *Oportunidades* on migration have found mixed results, especially with regard to domestic migration (Ishikawa, 2014; Angelucci, 2011). Generally, the characteristics of households that choose to move may be different from those who don't, and this selective migration could introduce bias if these characteristics are also related to educational outcomes. Although empirical models (1) and (2) include a control variable for whether a household has moved since the last survey panel, the effect may be more complex.

Thus, the following model is estimated to determine whether children and young adults ages 8-21 whose municipality experienced a greater increase in the homicide rate between 2005-2006 and when they were resurveyed in 2009-2012 were more likely to migrate. It also examines the impact of *Oportunidades* on migration.

(3) $$Logit(m_{ihj}) = \alpha_0 + \alpha_1 percentchangehomrate_j + \alpha_2 oportunidades\_prior_h + \alpha_3 realincome\_prior_h + \alpha_4 urban_h + \alpha_5 urban\_prior_h + \pi' X_{ih} + state\_prior_h + year_h + month_h + \varepsilon_{ihj}$$

In this model, m_{ihj} is the likelihood that a child or young adult migrated between the MxFLS2 and MxFLS3 panels. The model is estimated for individual i, a member of household h, residing in municipality j in the MxFLS2 panel from 2005-2006. $percentchangehomrate_j$ is the percent change in the homicide rate in their MxFLS2 municipality of residence from when they were surveyed in MxFLS2 to when they were surveyed in MxFLS3, regardless of whether they eventually moved to a different municipality or not. $oportunidades\_prior_h$ is a dummy variable for whether the individual's household was enrolled in *Oportunidades* in MxFLS2 and $state\_prior_h$ is a dummy variable for the state that they resided in at that time. $realincome\_prior_h$ and $urban\_prior_h$ make sure the household's prior income and prior type of municipality are take into account, and $urban_h$ shows the effect of the household ending up in an urban municipality in MxFLS3. That is, a household may be more likely to migrate if the end result is moving to an urban municipality from a rural municipality. As before, the vector X_{ih} includes other individual and household control variables: gender, indigenous identity, age, household size, parents' years of educational attainment, and whether the parents work.

Most of the independent variables included prove to be insignificant. However, individuals with a more educated father were significantly more likely to migrate, as were individuals who started in a rural municipality and those who ended in an urban municipality. These results hint at rural to urban migration. The year dummy variables are also significant, with individuals surveyed later in MxFLS3 more likely to have migrated. This is likely due to the increased time to track down and survey these families: they were more likely to be surveyed in a later year if they moved. The results are summarized in the following table:

Table 5. The impact of the percent change in the homicide rate, *Oportunidades* participation, and other controls on the choice to migrate.

Dependent Variable: Migrated between MxFLS2 and MxFLS3	
Independent Variables	
Percent change in the homicide rate (MxFLS2 municipality of residence)	-0.009 (0.40)
Prior Oportunidades participation	0.365 (1.38)
Current urban locality dummy	2.193*** (4.77)
Prior urban locality dummy	-2.334*** (5.45)
Prior real income	-0.052 (1.56)
Indigenous dummy	-0.076 (0.33)
Gender (male = 1)	0.109 (0.50)
Age	-0.067 (1.46)
Household size	-0.001 (0.01)
Mother's years of education	-0.012 (0.39)
Father's years of education	0.111*** (3.55)
Mother worked in last 12 months, dummy	-0.016 (0.06)
Father worked in last 12 months, dummy	-0.409 (1.09)
State dummies?	Yes

Year dummies?	Yes
Month dummies?	Yes
_cons	-7.961*** (4.69)
Pseudo R^2	0.3416
N	3,684

* p<0.1; ** p<0.05; *** p<0.01

One strategy to mitigate the impact of bias due to selective migration could be to assign level of violence exposure from the municipality of residence prior to migration, as demonstrated by Brown and Velásquez (2017) to avoid the concern that migration behavior may be driving the results. However, in this sample of 4,490 children and young adults, only 8 moved municipalities between the 2002 and 2005-2006 panels (0.2%), and 119 moved municipalities between the 2005-2006 and 2009-2012 panels (2.7%). Given this relatively low rate and the insignificant results of the migration model, this study continues to use the level of violence exposure of the municipality of residence at the time of survey for simplicity and to more directly estimate the impact of current local violence, in the context of potential fear and financial mechanisms that could affect education and labor outcomes.

iii. *Oportunidades* Dropout and Municipal Homicide Rate

Violence could also cause households to drop out of *Oportunidades* if increased fear of crime and victimization prevents them from fulfilling the required conditionalities or if it no longer makes financial sense for children and young adults to attend school rather than joining the labor force. To determine if changes in the homicide rate have an impact on the decision of households to drop out of *Oportunidades*, the following regression was designed:

$$(4)\ Logit(d_{ihjt}) = \alpha_0 + \alpha_1 percentchangehomrate_{jt} + \alpha_2 age_{it} + \alpha_3 realincome_{ht} + V'X_{ht} + state_{ht} + year_t + month_t + \varepsilon_{ihjt}$$

In the above specification, d_{ihjt} is the likelihood that an individual's household dropped out of *Oportunidades* between the prior survey panel and the current survey panel, given that they were enrolled in the program in the prior panel and did not move municipalities between panels. The model is estimated for individual i, a member of household h, residing in municipality j at time t, where t is the period when they were surveyed. $percentchangehomrate_{jt}$ is the percent change in the homicide rate in their municipality of residence between the two panels; age is the individual's age at time *t*; $realincome_{ht}$ is the transformed natural log of the household's income at time t; X_{ht} is the vector of household victimization variables; and $state_{ht}$, $year_t$, and $month_t$ are dummy variables for the state of residence and year and month of survey.

Running this regression with robust standard errors finds that households were significantly more likely to drop out of *Oportunidades* if they reported that gangs were frequently present in the neighborhood and significantly less likely to drop out if they felt safe at home. They were also more likely to drop out as age and real income increased. These results are summarized in the following table:

Table 6. The impact of the percent change in the homicide rate and other victimization variables on a household's decision to drop out of *Oportunidades*.

Dependent Variable: Dropped out of *Oportunidades* between the prior survey and the current survey	
Independent variables	
Percent change in the homicide rate	0.022 (0.57)
Gangs present in neighborhood	0.296** (2.38)
Feel safe at home	-0.385** (2.40)
Number of personal friend/family experiences with assault, robbery, and kidnapping in past 5 years	0.062 (1.51)
Age	0.057*** (3.29)
Real income	0.020* (1.72)
State dummies?	Yes
Year dummies?	Yes
Month dummies?	Yes

Constant	-3.467***
	(5.67)
Pseudo R^2	0.0954
N	2,796

* p<0.1; ** p<0.05; *** p<0.01

Although the R-squared value associated with this regression is relatively low at only 0.1, these findings should be taken into consideration when considering the results in the following section. The effect of participation in *Oportunidades* may depend on whether a household remains in the program. A household's decision to drop out appears to be related to its perception of violence and crime, although not directly tied to the percent change in the homicide rate.

Results

I. Educational Attainment

The fixed effects model for educational attainment from equation (1) finds that, for the 8-21 age group, the quartic root of the homicide rate and participation in *Oportunidades* both have a significant association with the percentage of possible years of education attained, but the sign on the homicide rate is reversed depending on which control variables are included.[10] In models (A) and (B), which use individual fixed effects but no time-variant controls, the homicide rate and the percent change in the homicide rate have a significant negative association with educational attainment. However, when an age control is added in model (C), the associations are significant and positive. This is true for all other models with added demographic controls, including model (E) with a municipality-level dummy rather than a state-level dummy. *Oportunidades* participation always has a significant, positive effect, while the interaction term between *Oportunidades* and the homicide rate is always negative.

These results are quite interesting because they appear to be in the opposite direction from some past research studies and the initial predictions of this study. The positive coefficient on the homicide rate variable for models (C) through (E) indicates that a greater increase in the

10. This model was also run using random effects, but the Hausman test rejected that the random effects model was a valid choice. Thus, fixed effects were chosen to analyze within-subject effects on years of educational attainment.

homicide rate is associated with more years of educational attainment. This may occur due to parents choosing to send their kids to school in order to keep them off the streets if drug-related violence and gangs are present. There may be bias if there is an unobserved municipality-level trend that is also correlated with homicide rates, but this effect still persists when including a municipality-level dummy. Interestingly, none of the crime perception variables are significant in models A-E, including the interaction between the homicide rate and the presence of gangs. This suggests that the significant homicide rate variable may indeed be picking up something other than perception of crime and risk, or that these variables do not vary enough over time for an individual for the fixed effects specification to pick them up.

The negative interaction term with *Oportunidades* indicates that a greater increase in the homicide rate does not have as much of an impact for those enrolled in *Oportunidades* compared with those not enrolled. This may be due to the initially higher educational attainment for *Oportunidades* participants, so they are already more likely to stay in school longer and the homicide rate does not have as much of an effect. Males do not experience as much of a positive association between years of education and increased homicide rates as females, which makes sense as they may be more likely to drop out of school to work as violence increases, especially if there is a financial mechanism involved.

Some specifications of the model include four interaction terms between the homicide rate and other variables: *Oportunidades*, gender, presence of gangs, and urban location. These interactions were chosen based on advisor feedback and past studies of factors that influence the effect of the homicide rate (i.e. gender from Brown and Velásquez, 2017). Running the interaction terms separately rather than all together does not change their significance.

Table 7. Results from fixed effects model (1) for the impact of the homicide rate, *Oportunidades*, and other variables on percent of possible years of educational attainment.

Outcome: Percentage of possible years of education					
Age group: 8-21 during MxFLS2 and MxFLS3					
Independent Variables	A	B	C	D	E
Quartic root of homicide rate	-0.043*** (11.86)	-0.026*** (5.14)	0.010* (1.86)	0.015** (2.33)	0.015** (2.32)

Percent change in homicide rate		-0.005***	-0.000	-0.001	-0.001
		(6.03)	(0.54)	(1.47)	(1.50)
Prior *Oportunidades* participation		0.018*	0.035***	0.034***	0.034***
		(1.76)	(3.61)	(3.52)	(3.43)
Oportunidades * homicide rate interaction		-0.011*	-0.012*	-0.012*	-0.011*
		(1.74)	(1.89)	(1.87)	(1.80)
Age			-0.016***	-0.038***	-0.038***
			(22.48)	(11.36)	(11.27)
Gender (male) * homicide rate interaction[11]				-0.014**	-0.014**
				(2.06)	(2.14)
Household size				-0.001	-0.001
				(0.40)	(0.47)
Real income (natural log)				0.000	0.000
				(0.97)	(0.95)
Migrated				0.023	-0.085
				(1.37)	(0.86)
Gangs present in neighborhood				0.009	0.010
				(0.76)	(0.80)
Feel safe at home				0.007	0.008
				(1.09)	(1.19)
Number of personal crime incidents				-0.000	-0.000
				(0.42)	(0.35)
Gangs present * homicide rate interaction				-0.002	-0.003
				(0.30)	(0.37)
Urban locality dummy				-0.017	-0.015
				(1.04)	(0.87)
Urban * homicide rate interaction				0.003	0.003
				(0.33)	(0.27)
Month dummies?	No	No	No	Yes	Yes

11. The gender indicator variable is not included by itself in this model because it is absorbed into the fixed effect; however, the interaction term is still included.

Year dummies?	No	No	No	Yes	Yes
State dummies?	No	No	No	Yes	No
Municipality dummies?	No	No	No	No	Yes
_cons	0.971***	0.951***	1.122***	1.487***	1.397***
	(199.05)	(140.22)	(112.65)	(29.04)	(29.46)
Within R^2	0.03	0.04	0.14	0.16	0.16
Between R^2	0.003	0.005	0.09	0.006	0.05
Overall R^2	0.0002	0.0006	0.10	0.009	0.05
N observations	8,980	8,980	8,980	8,980	8,980
N groups	4.490	4,490	4,490	4,490	4,490

* p<0.1; ** p<0.05; *** p<0.01

II. Current School Enrollment

Using the random effects logit model from equation (2), the percent change in the homicide rate since the last survey is found to be negatively associated with current school enrollment for children and young adults ages 8-21. The results are presented in Table 8. As with educational attainment, the association with the quartic root of the homicide ride is initially estimated to be negative (model G), and becomes positive when additional control variables are included (model H). But, when municipality-level fixed effects are included in model I, the homicide rate coefficient becomes statistically insignificant, and the percent change in the homicide rate becomes significant and negative. Parental education is found to be positively associated with enrollment, while age, household size, and the interaction of the homicide rate and the presence of gangs are negatively associated with enrollment. The *Oportunidades* coefficient and the interaction between *Oportunidades* and the homicide rate are not significant for the specifications with demographic controls (H and I).

The interaction term between the homicide rate and the presence of gangs is interesting in regression H, as this negative coefficient approximately cancels out the positive homicide rate coefficient for those households that perceive gangs present in their neighborhood. This means that a higher homicide rate had close to no impact on individuals that also had gangs frequently present in their neighborhood—the positive coefficient only holds for individuals that did not also report frequent presence of gangs. This may mean that an increase in the homicide rate not related to the presence of gangs may be correlated with some other underlying municipality-level characteristic that impacts school enrollment, and that is what the homicide rate coefficient is picking up. Including a municipality-level fixed effect gets rid of the statistical significance of both of these terms.

Given these results, Model J was run to determine the association between crime perception variables and current school enrollment directly, taking the homicide rate out of the equation. When the homicide rate and interaction variables are removed from model H, the presence of gangs becomes quite significant and negatively associated with current school enrollment. Gender also becomes significant, with a negative effect for males compared to females. This may indicate that the homicide rate is associated with some of these underlying characteristics.

Table 8. Results from random effects logit model using panel data (2) for the impact of the homicide rate, *Oportunidades*, and other variables on current school enrollment.

Outcome: Current school enrollment				
Age group: 8-21 during MxFLS2 and MxFLS3				
Independent Variables	G	H	I	J[12]
Quartic root of homicide rate	-0.311***	0.358**	0.227	
	(3.63)	(2.30)	(1.14)	
Percent change in homicide rate	-0.130*** (7.29)	-0.012 (0.58)	-0.068* (1.89)	
Prior *Oportunidades* participation	-0.706*** (4.10)	-0.125 (0.54)	-0.319 (0.26)	
Oportunidades * homicide rate interaction	-0.049 (0.42)	0.031 (0.20)	0.117 (0.69)	-0.069 (0.60)
Age		-0.741*** (19.19)	-0.752*** (19.13)	-0.736*** (19.35)
Indigenous		0.051 (0.45)	0.099 (0.78)	0.035 (0.31)

12. Models using just victimization perception variables (without homicide rate) were also run for all other dependent variables, but none of the key variables were found to be significant.

Gender (male = 1)	-0.005 (0.02)	-0.082 (0.36)	-0.243** (2.39)
Gender (male) * homicide rate interaction	-0.179 (1.21)	-0.153 (1.03)	
Real income (natural log)	0.010 (0.85)	0.001 (0.08)	0.009 (0.81)
Household size	-0.075*** (3.20)	-0.068*** (2.82)	-0.073*** (3.16)
Mother's years of education	0.141*** (7.53)	0.136*** (7.02)	0.140*** (7.55)
Father's years of education	0.174*** (9.88)	0.166*** (9.16)	0.173*** (9.94)
Migrated	-0.249 (0.62)	1.110 (1.34)	-0.332 (0.85)
Gangs present in neighborhood	0.191 (0.63)	0.072 (0.22)	-0.313*** (2.67)
Feel safe at home	0.279 (1.62)	0.251 (1.41)	0.261 (1.53)
Number of personal crime incidents	0.026 (1.25)	0.026 (1.22)	0.025 (1.21)
Gangs present * homicide rate interaction	-0.371* (1.84)	-0.269 (1.27)	
Urban locality dummy	-0.328 (0.94)	-1.340** (2.11)	0.138 (1.06)
Urban * homicide rate interaction	0.284 (1.32)	0.560 (1.45)	
Month dummies?	Yes	Yes	Yes
Year dummies?	Yes	Yes	Yes
State dummies?	Yes	No	Yes
Municipality dummies?	No	Yes	No

_cons	2.200*** (15.90)	14.428*** (7.70)	13.421*** (6.87)	15.080*** (8.08)
lnsig2u	0.674*** (5.34)	0.703*** (3.29)	0.441* (1.75)	0.672*** (3.13)
N observations	6,632	6,630	6,578	6,630
N groups	3,316	3,316	3,294	3,316

* p<0.1; ** p<0.05; *** p<0.01

III. Completion of Compulsory Education

The logit model for compulsory education finds a large and statistically significant, negative association between the homicide rate and the likelihood for a young adult to complete compulsory schooling through grade 9 (presented in Table 9, model N). The effect is statistically significant only when including the municipality-level fixed effect rather than the state-level fixed effect. Household size is also negatively associated with the likelihood of completion, while age and parental years of education are positively associated. This result reveals additional evidence that supposed positive effects of the homicide rate on educational attainment and school enrollment may be due to unobserved municipality-level characteristics, rather than the actual influence of the homicide rate.

Table 9. Results from logit model for the impact of the homicide rate, *Oportunidades*, and other variables on completion of compulsory education for young adults ages 15-16 at time of MxFLS3.

Outcome: Completion of compulsory education				
Age group: 15-16 during MxFLS3				
Independent Variables	K	L	M	N
Quartic root of homicide rate	0.224 (1.37)	0.151 (0.46)	0.137 (0.39)	-3.528** (2.33)
Percent change in homicide rate	-0.013 (0.62)	0.025 (0.50)	0.020 (0.42)	-0.226 (1.26)
Prior *Oportunidades* participation	-0.037 (0.10)	0.859* (1.83)	0.766 (1.57)	0.625 (0.97)
Oportunidades * homicide rate interaction	-0.204 (0.91)	-0.257 (0.88)	-0.264 (0.87)	-0.347 (0.85)

Age		0.673***	0.674***	0.851***
		(3.69)	(3.70)	(3.53)
Indigenous		-0.083	-0.107	-0.133
		(0.41)	(0.54)	(0.46)
Gender (male = 1)		-0.084	-0.120	-0.327
		(0.18)	(0.25)	(0.56)
Gender (male) * homicide rate interaction		-0.353	-0.330	-0.461
		(1.19)	(1.08)	(1.20)
Real income (natural log)		-0.002	0.001	-0.005
		(0.08)	(0.04)	(0.17)
Household size		-0.080**	-0.081**	-0.087
		(2.00)	(2.02)	(1.60)
Mother's years of education		0.133***	0.139***	0.173***
		(3.99)	(4.08)	(3.76)
Father's years of education		0.113***	0.113***	0.190***
		(3.98)	(3.96)	(4.75)
Migrated		0.861	1.005	4.664
		(1.29)	(1.47)	(1.44)
Gangs present in neighborhood		0.438	0.518	0.102
		(0.72)	(0.84)	(0.13)
Feel safe at home		0.226	0.210	0.002
		(0.67)	(0.62)	(0.01)
Number of personal crime incidents		0.015	0.022	0.008
		(0.20)	(0.26)	(0.09)
Gangs present * homicide rate interaction		-0.183	-0.199	0.117
		(0.46)	(0.49)	(0.23)
Urban locality dummy			-0.658	-2.384
			(1.03)	(0.57)
Urban * homicide rate interaction			0.152	1.690
			(0.41)	(0.64)
Month dummies?		Yes	Yes	Yes
Year dummies?		Yes	Yes	Yes
State dummies?		Yes	Yes	No
Municipality dummies?		No	No	Yes
_cons	0.712***	-11.440***	-11.444***	-8.155*
	(2.88)	(3.77)	(3.77)	(1.80)
Pseudo R^2	0.006	0.19	0.19	0.30

N observations	1,091	822	822	652

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

IV. Labor Force Participation

Finally, the random effects logit model from equation (2) is applied to labor force participation.[13] The percent change in the homicide rate is only statistically significant (greater change in homicide rate associated with higher likelihood of working) when no control variables are included. Higher parental education is associated with a lower likelihood of working, which makes sense as more highly educated parents may be more likely to keep their children in school for longer. Age is associated with a higher likelihood of working; however, the effects of the homicide rate and of *Oportunidades* are not clear.

Table 10. Results from random effects logit model using panel data (2) for the impact of the homicide rate, *Oportunidades*, and other variable on labor force participation, i.e. whether an individual worked in the past 12 months.

Outcome: Worked in the past 12 months		
Age group: 14-17 during MxFLS3		
Independent Variables	O	P
Quartic root of homicide rate	0.187 (1.01)	0.124 (0.39)
Percent change in homicide rate	0.079*** (2.92)	0.033 (0.71)
Prior *Oportunidades* participation	0.078 (0.20)	-0.098 (0.22)
Oportunidades * homicide rate interaction	0.315 (1.23)	0.012 (0.04)
Age		0.671*** (7.89)
Indigenous		0.043 (0.21)
Gender (male = 1)		0.470 (1.06)

13. A model with municipality-level fixed effects could not be estimated for labor force participation because too many observations were dropped due to perfect prediction based on municipality (i.e. many municipalities perfectly predicted failure to work). This resulted in log-likelihood iterations that were not concave, and the final model could not be determined. As the most successful iterations of the other models involved municipality fixed effects, this is a big limitation.

Gender (male) * homicide rate interaction		0.225 (0.79)
Real income (natural log)		-0.007 (0.35)
Household size		-0.028 (0.74)
Mother's years of education		-0.079** (2.54)
Father's years of education		-0.105*** (3.65)
Migrated		-0.257 (0.31)
Gangs present in neighborhood		-0.467 (0.74)
Feel safe at home		-0.376 (1.26)
Number of personal crime incidents		-0.075 (0.98)
Gangs present * homicide rate interaction		0.361 (0.89)
Urban locality dummy		0.563 (0.83)
Urban * homicide rate interaction		-0.501 (1.24)
Month dummies?		Yes
Year dummies?		Yes
State dummies?		Yes
_cons	-3.346*** (12.40)	-11.327*** (7.64)
lnsig2u	-10.619 (0.38)	-9.906 (0.48)
N observations	3,230	3,223
N groups	1,615	1,615

* p<0.1; ** p<0.05; *** p<0.01

Conclusion

This study attempts to identify whether Mexico's conditional cash transfer program, *Oportunidades*, could mitigate the effects of the spike in drug-related violence using a difference-in-differences approach with individual-level panel data. Previous papers have found negative or ambiguous effects of the violence on educational outcomes, and identified underlying financial or fear-based mechanisms. These could be partially counteracted by *Oportunidades*. This study adds to the existing body of knowledge by examining the effects of the violence on multiple short-term and long-term measures of education and labor outcomes, in relation to a major CCT program.

The models presented in this paper reveal mixed effects of violence, *Oportunidades* participation, and their interaction depending on the outcome variable and exact specification. Increased homicides may be associated with increased educational attainment, with a larger effect for individuals not participating in *Oportunidades,* as recipients already experience greater educational attainment. This significant, positive coefficient may occur due to parents choosing to send their kids to school in order to keep them off the streets if drug-related violence and gangs are present. Qualitatively, drug cartels have focused on recruiting young men and boys, which may lead to parents keeping them in school (Burnett, 2009), but quantitatively, the cause behind this observed effect is unclear. Another possibility is bias, as the homicide rate may really be a marker for other municipality-level characteristics that impact educational attainment. Still, the significant, positive coefficient calls into question the robustness of past estimates for effects of Mexico's violence on educational attainment, as the effect persists when including municipality-level fixed effects.

The results related to completion of compulsory education and current school enrollment are more in-line with past findings. When using municipality-level fixed effects, increased homicide rates are associated with lower likelihood of completing compulsory education and a greater change in the homicide rate is associated with lower school enrollment. For both of these outcomes, *Oportunidades* participation and the interaction term between *Oportunidades* and the homicide rate are not significant. None of the key variables in the labor force participation model were significant. The municipality-level fixed effects play a key role in interpreting these results, as the model for school enrollment without these effects found a significant positive association between the homicide rate and enrollment. Without a municipality fixed effect, the homicide rate variable appears to pick up something else.

The measurement of crime perception is another limitation to this study. The homicide rate is not highly correlated with the variables related to perception of crime risk and victimization, and these variables are not significant in most of the models. This result appears to reject the theory that increased perception of risk and violence are associated with homicides and are driving changes in behavior; however, the presence of gangs and feelings of safety at home do seem to affect a household's decision to drop out of *Oportunidades*. Additionally, one model for school enrollment that removed the homicide rate found that the presence of gangs did have a strong negative association with likelihood of school enrollment. It is also possible that the selected victimization variables may not be that accurate a measure of actual crime perception. As the homicide rate is not highly correlated with perception of victimization, there may alternatively be a financial mechanism associated with the homicide rate. However, this study does not find a significant impact of the violence on labor to suggest such a trend.

The contribution of this work is the novel examination of the relationship between drug violence and conditional cash transfers using a difference-in-differences, panel data approach. Despite many limitations, this study affirms the strategy of municipality-level fixed effects, and finds that *Oportunidades* does have a significant positive effect on years of educational attainment, even in a turbulent and violent time period, so the increase in violence may not alter some effects of the program. Drug-related violence in Mexico shows no sign of abating, nor does the widespread distribution of *Oportunidades* benefits. As both of these trends continue to prevail, it is crucial to continue researching the best way to estimate their impact and underlying mechanisms in order to better understand which policy programs or methods might be most effective in the future.

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Appendix A. Principal component analysis for crime and victimization variables

Seven components with eigenvalues > 1 are identified as most significant for further analysis

Table A.1. Principal components/correlation
Number of observations = 15,744 Number of components = 21
Trace = 201 Rho = 1.0000
Rotation: (unrotated = principal)

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.72958	1.1561	0.13	0.13
Comp2	1.57348	0.222803	0.0749	0.2049
Comp3	1.35068	0.0908729	0.0643	0.2692
Comp4	1.2598	0.0377867	0.06	0.3292
Comp5	1.22202	0.19015	0.0582	0.3874
Comp6	1.03187	0.0243494	0.0491	0.4365
Comp7	1.00752	0.0390438	0.048	0.4845
Comp8	0.968473	0.0410179	0.0461	0.5306
Comp9	0.927455	0.0283053	0.0442	0.5748
Comp10	0.89915	0.0106921	0.0428	0.6176
Comp11	0.888458	0.0289024	0.0423	0.6599
Comp12	0.859555	0.0253162	0.0409	0.7009

Comp13	0.834239	0.00123381	0.0397	0.7406
Comp14	0.833005	0.0446542	0.0397	0.7803
Comp15	0.788351	0.0378473	0.0375	0.8178
Comp16	0.750504	0.0340919	0.0357	0.8535
Comp17	0.716412	0.0573231	0.0341	0.8876
Comp18	0.659089	0.00479222	0.0314	0.919
Comp19	0.654297	0.105926	0.0312	0.9502
Comp20	0.548371	0.0506634	0.0261	0.9763
Comp21	0.497707	.	0.0237	1

Table A.2. Principal components (eigenvectors), weights for significant component calculation. The most important variables for each component (weight with absolute value of greater than 0.25) are highlighted in blue.

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7
vlh01a: buildings abandoned	0.2523	-0.0554	0.1087	-0.138	-0.0143	0.0912	0.3094
vlh01b: gather gangs/ factions	0.3977	-0.2179	0.0512	-0.1094	-0.181	0.0409	0.1001
vlh01c: drug use in streets	0.3857	-0.2129	0.0717	-0.0293	-0.1679	0.0548	0.1341
vlh01d: prostitutes in streets	0.2703	-0.1583	0.1089	-0.1153	-0.0985	0.0532	-0.1275
vlh01e: neighbor conflicts	0.3612	-0.2045	0.0367	-0.026	-0.1465	0.0442	-0.0882
vlh01f: neighbor protection groups	0.1529	0.0381	0.1924	0.2527	0.2731	0.1845	-0.0091
vlh01g: guards/ paramilitaries	0.176	0.0197	0.2006	0.1007	0.5605	0.1535	-0.0868
vlh01h: military reserves/ soldiers	0.185	0.0755	0.2273	-0.0092	0.5391	-0.0121	-0.0478
vlh01i: armed neighbors in streets	0.2886	-0.0853	0.015	-0.0349	-0.0134	-0.0767	-0.2995
vlh04: feel safe at home	-0.1741	0.1207	0.1375	0.0071	0.0248	0.2975	0.4323
vlh05: ask neighbor to look after house	0.0915	0.306	0.3312	0.4119	-0.1791	-0.2514	-0.0169
vlh06: leave lights on for security	0.1301	0.3536	0.3227	0.2801	-0.2606	-0.2406	-0.088
vlh07a: house wire/sting/grating /colter	0.0084	0.3592	0.1854	-0.2938	-0.1747	0.1846	-0.1867
vlh07b: house window bars	0.0745	0.3942	0.1311	-0.3001	-0.1325	0.2045	0.0297

vlh07c: house security system	0.0048	0.1965	-0.0621	-0.1943	-0.0072	0.455	-0.4732
vlh08a: fam/ friend robbed last 5 years	0.2778	0.2858	-0.3968	0.1416	-0.0127	0.0412	0.0516
vlh08b: fam/ friend assaulted last 5 years	0.261	0.2698	-0.4848	0.13	0.0201	0.0069	0.0625
vlh08c: fam/ friend kidnapped last 5 years	0.1511	0.203	-0.3916	0.0886	0.1524	-0.0659	0.0038
indigenous: member of indigenous group	-0.0335	-0.1966	-0.044	0.4909	-0.0912	0.2578	-0.1921
ln_realincome: natural log of household's real income	0.0867	0.103	0.0422	0.1277	-0.0559	0.357	0.481
quartic_homrate: quartic root of the municipality-level homicide rate in the 12 months prior to survey	0.1263	0.1456	0.0175	-0.3384	0.2101	-0.4754	0.1521

While the relationship of the variables within the seven components is not completely clear, there is some grouping that can be identified and attributed to certain factors. For example, Component 2 appears to be tied to safety measures such as leaving on lights and asking neighbors to watch the house, along with personal experiences with crime. Component 6 is primarily composed with household characteristics such as income and indigenous background, along with the actual homicide rate, security systems and whether the household member feels safe at home. Still, the general lack of clear patterns and interpretability of the components resulted in their exclusion from the final empirical analysis.

Appendix B. Correlations between independent variables

Table B.1. Pairwise correlations between all independent variables used in regression, excluding interaction terms. All correlations with absolute value greater than or equal to 0.2 are highlighted in blue.

	Quartic homicide rate	Percent change homicide rate	Oportunidades prior	Age	Indigenous	Gender	Real income (natural log)	Urban
Quartic homicide rate	1.00							
Percent change homicide rate	0.31	1.00						
Oportunidades prior	-0.03	-0.01	1.00					
Age	0.17	0.21	0.07	1.00				
Indigenous	-0.17	-0.04	0.20	0.001	1.00			
Gender	-0.03	0.0002	0.007	0.009	-0.007	1.00		
Real income (natural log)	0.02	-0.03	-0.06	-0.07	-0.01	-0.006	1.00	
Urban	0.23	0.08	-0.38	-0.01	-0.17	-0.01	0.10	1.00
Household size	-0.02	-0.03	0.20	0.002	0.20	-0.03	0.05	-0.11
Mother's years of education	0.10	0.04	-0.29	-0.06	-0.21	-0.001	0.09	0.29
Father's years of education	0.07	0.04	-0.33	-0.06	-0.17	0.0005	0.10	0.33
Migrated	0.05	0.15	-0.007	0.05	-0.002	-0.0004	0.004	0.10
Gangs present	0.07	0.02	-0.12	0.02	-0.03	-0.01	0.04	0.25
Feel safe at home	-0.02	-0.008	0.002	-0.002	-0.01	0.01	0.01	-0.03
People in locality trustworthy	-0.07	-0.017	0.07	0.01	0.03	0.01	-0.008	-0.17
Number of personal crime incidents	0.06	0.03	-0.06	0.02	-0.04	-0.005	0.04	0.09

Table B.1., continued from previous page

	Household size	Mother's years of education	Father's years of education	Migrated	Gangs present	Feel safe at home	People in locality trustworthy	Number of personal crime incidents
Household size	1.00							
Mother's years of education	-0.28	1.00						
Father's years of education	-0.27	0.63	1.00					
Migrated	-0.02	0.01	0.03	1.00				
Gangs present	0.004	0.04	0.07	0.02	1.00			
Feel safe at home	-0.005	0.02	0.02	-0.03	-0.15	1.00		
People in locality trustworthy	0.01	-0.05	-0.06	-0.02	-0.24	0.19	1.00	
Number of personal crime incidents	-0.04	0.12	0.09	0.01	0.11	-0.10	-0.08	1.00

Correlations between independent variables are examined to reduce the risk of multicollinearity. Overall, there is little correlation between independent variables as only four pairs have a correlation over 0.3 (absolute value). The only variables with a correlation higher than 0.5 were father's years of education and mother's years of education, with a correlation of 0.63. This makes sense given the socioeconomic status and composition of many households. There is also a fairly large negative correlation between prior *Oportunidades* participation and whether the household lives in an urban locality at -0.38. This is due to the way that *Oportunidades* is distributed in rural and urban areas, but could potentially be high enough to influence results.