Internal Migration and Drug Violence in Mexico [*]

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Abstract

We study the effects of drug-related violence on internal migration in Mexico between 1995 and 2015. High homicide rates after 2007 reduced net migration into violent municipalities. This effect is driven by lower inflows, consistent with a high homicide rate being a disamenity, and with large migration costs. The variation generated by cartel conflict over drug routes identifies causal estimates of violence on migration. To quantify the effect of high homicide rates on migration across Mexico's system of cities, we estimate a spatial equilibrium model following Diamond (2016). We find that unskilled workers are the most affected, and are willing to accept wages 1% lower to decrease the homicide rate by 3%, and must receive wages at least 70% larger at destinations to be willing to move. Most welfare costs are driven by losses incurred by inframarginal individuals who stay in now-violent municipalities. The estimated welfare loss in partial equilibrium is equivalent to around 1.4% of GDP per year in 2010. Large moving costs play a central role, as individuals have few chances to substitute away from a worsened local environment. General equilibrium effects decrease welfare further, as destination wages decrease with population inflows. We estimate an elasticity of local labor demand of .89, and find that general equilibrium effects had negligible welfare consequences in the presence of moving costs.

1 Introduction

Since the start of the twenty first century, organized crime has caused as many homicides as armed conflict. While less destructive than war, the violence that organized criminal groups carry out, often against other criminal groups, is also harmful for the communities that experience them (United Nations Office on Drugs and Crime 2019). Homicide related to organized crime is an especially important development challenge in the Americas. There, drug trafficking organizations fight violently for control of routes and shipments, contributing to the region having the largest homicide rate in the world as of 2019. Homicides disrupt communities' social, economic and institutional life (ibid), inducing individuals to move away and cause ripple effects within countries –even if crime is confined in space. In order to understand the effect of homicides on a country's welfare and population, it is key to study individuals' migration decisions, and their ripple effects.

This paper studies the effects of homicide rates on internal migration in Mexico between 1995 and 2015. The homicide rate in Mexico almost tripled between 2000 and 2015. As conflict between drug trafficking organizations (DTOs) intensified, homicides became a public problem.[1] This kind of violence became a salient feature of some cities and day-to-day life deteriorated as a result. By 2011, over 60 percent of Mexicans identified insecurity as their main concern, over poverty and employment (ENVIPE 2011). However, violence did not increase everywhere - it rose most in municipalities close to drug traffic routes. This uneven change created opportunities for individuals to decrease their exposure to violence by adjusting their migration decisions.

We first analyze migration in the reduced form and later estimate a structural model to

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[1]DTOs fought in streets and businesses, leaving bodies in public spaces as threats to opposing groups. See for instance Villareal's chapter in Campbell 2016 for a description on day-to-day life in a Mexican city exposed to high homicide rates.

quantify the welfare and population effects of homicides. The model also lets us understand the role of moving costs and general equilibrium effects. First, we study how municipality level inflows and outflows changed with violence. Changes in DTO alliances and the location of conflict on drug trafficking routes serve to instrument for violence. As DTOs join or splinter, conflicts over routes change in intensity and location. In turn, municipalities that find themselves in a region with more conflict face higher homicide rates, independently of other local characteristics. Using this variation, we find high homicide rates cause net migration away from locations, driven mainly by lower inflows. This is consistent with the homicide rate acting like a disamenity, and with large costs of relocation. Unskilled workers are most affected by the increase in violence.

Second, we estimate a structural spatial equilibrium model, following Diamond 2016. Migration choices depend on relative characteristics, which are well captured by a discrete choice model. We use migration shares to destinations to identify the mean utility of municipalities, and the share of migrants to pin down the cost of moving. Using our conflict measure and Bartik shocks as instruments for violence and wages, we identify how much individuals value wages, violence, and moving costs. Individuals reveal to be willing to accept a 1% decrease in monthly wages to decrease the local homicide rate by 3%. Moving is very costly: wages must be 70% higher at destinations for unskilled workers to be willing to make the move. This is consistent with existing research on spatial equilibrium in developing countries, where large gaps in observed predictors of quality of life do not generate large reallocations of population across space (Gollin, Kirchberger, and Lagakos 2017a and Chauvin et al. 2016).

With the estimated model, we study the role moving costs and general equilibrium (GE) play in determining the effect of violence. First, we provide an estimate of the total welfare loss caused by the increase in violence, and the margins through which migration responded.

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We estimate the welfare cost to be 1.4% of GDP in 2010, with a majority of individuals not altering their migration decisions due to high migration costs. The estimated welfare costs are similar when individuals have no adjustment margins. In particular, with infinite moving costs, welfare losses would only be 16% larger than under estimated moving costs. Violence affected migration mainly by modifying migrant destinations, rather than increasing displacement.[2] The number displaced has attracted significant attention from government agencies, human rights advocate groups, and academics in other social sciences (Díaz Pérez and Romo Viramontes 2019, Pérez Vázquez et al. 2019, Rubio Díaz-Leal 2014, IDMC 2012). We are the first to estimate the amount of displacement using migration decisions and a model. We estimate around 2.4 million displaced unskilled individuals between 2005 and 2010. These results point to the limitations of studying the number displaced as the main demographic outcome of violence. Social costs can be large in the presence of little displacement, and migration patterns can be distorted in other ways as well - such as altering destination choices. Welfare losses are large (1% of GDP) even if moving costs are zero, as many individuals still move to violent locations for idiosyncratic reasons.

Last, we study general equilibrium effects. To estimate the elasticity of wages to migration inflows we use predicted outflows and historical migration patterns (following Derenoncourt 2019) to instrument for inflows at destinations. Using our estimates of the elasticity of local labor demand, we calculate a counterfactual equilibrium distribution of population, letting local wages adjust. We find that general equilibrium effects minimally modify the effect of violence on population and welfare. Welfare losses from violence are only 3% larger with GE adjustments than without.

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[2]The number displaced is commonly reported as a measure of the intensity or social cost of conflict –for example see the United Nations' World Humanitarian Data and Trends report, 2016.

The rest of the paper is structured as follows. Section I discusses related literature. Section II describes our data. Section III presents reduced form evidence about the relationship between violence and migration inflows and outflows in Mexican municipalities. It also introduces our instrumental variable for violence, predicted drug route conflict. Section IV introduces and estimates the model of labor supply, labor demand, and estimates labor demand elasticities at destinations. Section V shows our counterfactuals, and discusses the welfare effect of violence and its interaction with moving costs. Section VI concludes.

2 Literature Review

Our paper contributes to two branches of the literature in economics. The first studies the effects of conflict on economic outcomes.[3] We add to this literature by studying the migration consequences of the low intensity, but long lasting violence generated by organized crime. So far in the twenty first century organized crime has caused as many killings as armed conflict, making this contribution especially important to understand the cost of contemporary conflict. (United Nations Office on Drugs and Crime 2019). Particularly, our findings speak to the growing literature on the effects of drug violence in Mexico on different socioeconomic indicators, such as economic growth (Enamorado, López-Calva, and Rodríguez-Castelán 2014; Bel and Holst 2018); labor force participation, local businesses, local rates of unemployment, and electricity per capita (Robles, Calderón, and Magaloni 2013); housing prices (Ajzenman, Galiani, and Seira 2015); foreign investment in financial services, commerce, and agriculture (Ashby and Ramos

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[3]Previous work studies the consequences of conflict on outcomes such as per capita GDP (A. Abadie and J. Gardeazabal 2003; Gaibulloev and Sandler 2009; Gaibulloev and Sandler 2008), foreign direct investment (Alberto Abadie and Javier Gardeazabal 2008; Enders, Sachsida, and Sandler 2006), global capital markets (Chen and Siems 2004), consumption per capita (Eckstein and Tsiddon 2004), and human capital accumulation (Chamarbagwala and Morán 2011).

2013); and educational performance (Michaelsen and Salardi 2018; Orraca-Romano 2018).

Our work relates most closely to two papers that study the effect of drug violence on migration flows. Ríos 2018 first documented that drug violence is related to larger errors in population projections, suggesting negative net migration in violent municipalities. Basu and Pearlman 2017 estimate the impact of violence on gross out migration rates at the municipal and state levels using the 2010 Mexican Census and labor surveys. They find a puzzling muted response of out migration to violence in the municipal cross-section. They also find little evidence of increased international migration at the municipal level. We build on this strand of work in several ways. First, by studying out and in-migration separately and by using municipal-level panel variation, we are able to show that both results are compatible. We show net domestic migration into violent municipalities decreases, driven by lower inflows. Second, we leverage a different source of exogenous variation to violence by constructing an instrument that exploits changes in drug cartel alliances and the location of conflict on drug trafficking routes. Finally, and more importantly, by estimating a structural model we can estimate the welfare effects of increased violence and study their channels more closely. This allows us to provide estimates of the number of Mexicans displaced by violence, which has received independent attention.

A recent report by CONAPO (Díaz Pérez and Romo Viramontes 2019)[4] reviews this literature. Existing work focuses on using survey data on individuals' migration behavior and their reported motives. Estimates of the number displaced range from the order of 100 thousand over a 13 year period to 800 thousand between 2009 and 2010. The large variation in results calls into question the precision of the amounts of violence-induced migration stated in surveys. Possible explanations for this include migration depending on several factors, individuals misreporting

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[4](Mexican Population Council, a dependency of the Mexican government.)

motives, and inconsistent definitions or methods across surveys. In contrast, we estimate the number displaced using a model and migration choices.

Second, our paper contributes to the literature that studies the spatial equilibrium framework in the developing world. Chauvin et al. 2017 test the spatial equilibrium hypothesis in Brazil, China, and India and conclude that the implications of the standard spatial equilibrium model are rejected in some countries. Gollin, Kirchberger, and Lagakos 2017b find that a spatial equilibrium is not the right description for twenty developing countries in sub-Saharan Africa. We add to this literature by documenting evidence of large migration costs in Mexico.

3 Data

This section describes our data. We study the panel of all Mexican municipalities and three migration periods. These cover the years between 1995 to 2015. All our sources are public.

Migration is our main outcome variable. Individual data on migration, along with years of education, wage, and employment by occupation comes from decennial Censuses (2000, 2010), an Intercensal Survey (2015) and Maldonado and Grau 2013. All surveys are representative at the municipal level. We observe individuals' municipality of residence at the time of the survey and five years prior. We define $inflows_{jt}$ for municipality j at year t as the number of individuals who lived in municipality j at year t, but not at year $t-5$. By analogy, $outflows_{jt}$ is the number of individuals living in municipality j at time $t-5$, but not at time t. In the labor supply estimation, we use population flows between all municipality pairs as migration choices.

We study migration behavior separately for low and high skill. This serves two purposes. First, we expect different behavior from the two types –in other settings, mobility is much larger

for the highly educated. In addition, education proxies for socioeconomic status and we expect the effect of violence to depend on it. We classify individuals as skilled or unskilled based on their education. A skilled person in our definition has 19 years of education or more, which corresponds to finishing a four year college program in Mexico. We calculate average wages for each j and t by skill group. When studying these subgroups separately, we use their conditional mean wage.

Our object of interest is the effect of violence. We measure violence using the local homicide rate. The National Statistics Office (INEGI) reports homicide rates per 100,000 population for each municipality and year. We average the homicide rate over each five-year migration period, and take logarithms to construct a municipality level measure of violence.[5] The Center for Economic Research and Teaching (CIDE) has made a separate dataset with murders attributed by a government panel to DTO's. We chose the more comprehensive measure of all homicides from INEGI instead for two reasons. First, CIDE's measures only covers 2006-2010, and second, the process of classifying homicides as "drug-related" is not transparent.

We construct lists of drug traffic origins and destinations as inputs to our model of cartel conflict. Some drugs are more valuable to drug trafficking organizations (DTOs) than others, and so are more likely to attract conflict (Castillo, Mejía, and Restrepo 2018, DEA 2015). For this reason, we expect routes that transport different kinds of drugs to cause different levels of violence, and model them separately.

Our data allows us to separately infer the source locations of marihuana, poppy seed, and

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[5]Homicide data is available beginning in 1998. Thus, for the 1995-2000 migration period, the homicide's average corresponds to 1998 to 2000. Since some municipalities report zero homicides in some periods, we add the smallest observed homicide rate to all municipality years. This normalization guarantees that the number of municipalities is constant in every period.

imported drugs, such as cocaine.[6] Marijuana, heroin, and cocaine make up the bulk of the drug trade from Mexico into the United States. The Mexican Secretariat of Defense measures the area of marijuana and poppy fields destroyed in its eradication efforts for each municipality (Sedena 2018). We define production locations as those in the top 5% by total eradicated area over our study period.[7] This set of municipalities accounts for over 80% of all eradicated area, pointing to concentrated production in a few rural regions.

DTOs import drugs from other countries to bring them into the US. Cocaine is a notable example, as it is not produced in Mexico. Imported drugs come into the country through maritime ports, illegal landing strips, international airports, railroads, etc. Due to the high volume of freight transport, we focus on maritime ports. Thus, we define drug import locations as ports with substantial cartel presence, according to the DEA's 2015 National Drug Threat Assessment (NDTA) map on Areas of Dominant Influence and Key Areas of Conflict. This report also lets us identify the predominant cartels present in each location. Since we compute routes over land, we ignore ports in the south-east. These are far from points of entry into the US and unlikely to serve as origins for land traffic routes.

According to the DEA, most of the drugs moving from Mexico to the US enter through land. The NDTA identifies points of entry (POE) into the US with significant cartel presence on the border between Mexico and the US. These define drug route destinations in our model.

Finally, we construct Bartik shocks to instrument for wages in the preference parameter estimation. These are calculated using municipality level employment shares by sector from the 1995 Intercensal Survey and the Economic Census of 2004 and 2009.

Rent is notably absent from the regressions and model, due to specific features of Mexican

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[6]Poppy seed is the main input in heroin production.
[7]Approximately half of all municipalities report destruction of crops.

housing institutions. The rate of Mexicans who live in a family-owned home is substantial, approximately 67.7 percent.[8] The Mexican Federal government promotes homeownership through several programs, including mandatory paycheck deductions into a mortgage fund for all formal workers and subsidized loans. Self-built homes in slums or unregulated lands are also typical. For these reasons, local rents are not as important in determining migration choices as in more developed countries. Rent data is notably sparse in national surveys and is not available for every municipality. The rent data we use is from the National Household Income and Expenditure Survey of 2010.

4   Reduced Form Results: Homicides and Migration

Homicides increased sharply in Mexico after 2007. Figure 1 shows monthly homicides from 2000 to 2016. Aside from the direct effect on homicide victims, rising violence also affected local residents. As homicides became more frequent, they were also prone to be carried out in public, or have victims' bodies displayed or abandoned in roads, bridges, or streets. These drug related homicides cause increased fear and a sense of insecurity (Gutiérrez-Romero 2015), and are related to depression symptoms in the local population (Martínez and Laura Helena Atuesta 2018). Sociological work documents how fear and "spectacular violence" hindered daily life in some Mexican cities (Campbell 2016).

   If households dislike living where the homicide rate is high, we should observe net migration out of those locations, all else constant. This is especially true if violence did not increase across the whole country, allowing individuals to substitute away from violence. Figure 2 shows the resulting violence was concentrated in space, resulting in large regional differences in log mean

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[8]2015 Intercensal Survey, INEGI.

**Figure 1:** Monthly homicides in Mexico, 2000-2016
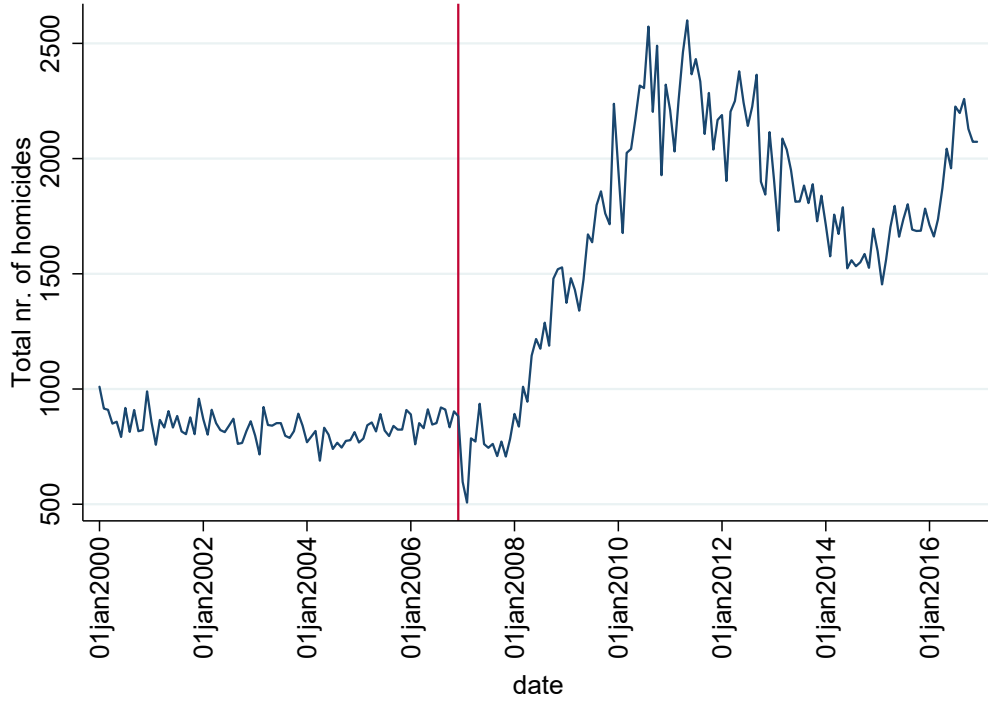
homicide rates in 2010.

Table 1 shows measures of mean municipality violence and total internal migration for the three periods reported in the Censuses: 1995-2000, 2005-2010, and 2010-2015. The mean municipal homicide rate more than doubled between the first and second period, and increased further in the third. During this period, we also observe a substantial increase in the total number of internal migrants, defined as the number of individuals who report changing municipality of residence in the five years before the census date.

Figure 3 shows binscatter plots of inflows and outflows against the log homicide rate controlling for time and municipality fixed effects and local wages, following Cattaneo et al. 2019.

Figure 2: Log homicide rates, 2010
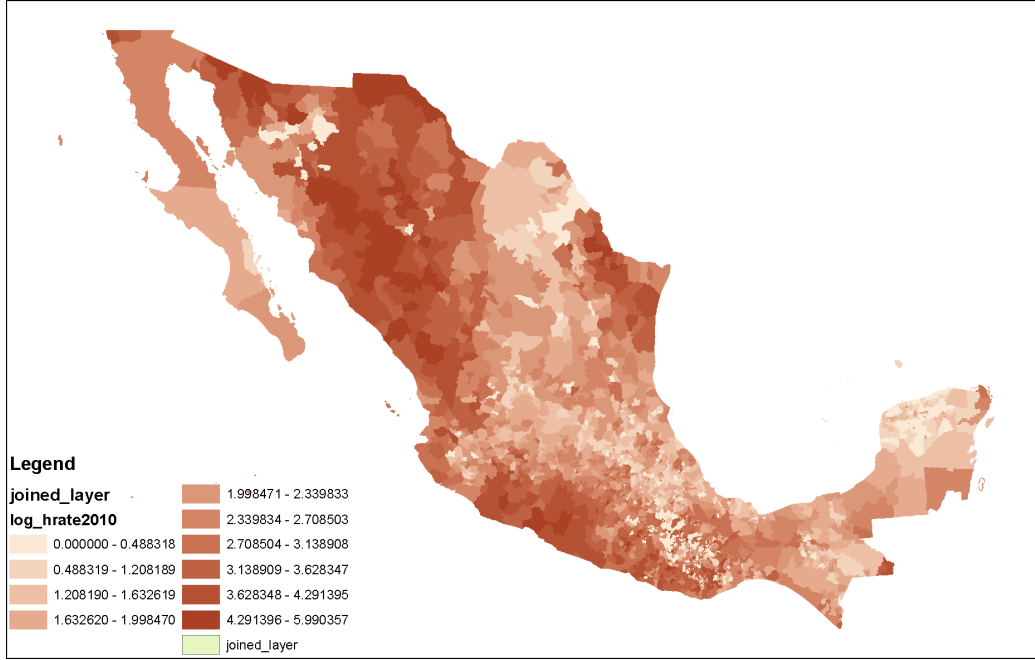
As expected, inflows tend to be more negative as homicides increase. The relationship between outflows and homicides is less clear cut.

Table 4 shows the OLS estimates of the effect of log mean homicide rate on log inflows and outflows, controlling for local wages, municipality fixed effects, and time fixed effects. Let the outcome migration variable be $Y_{jt} \in \{\ln(outflows)_{jt}, \ln(inflows)_{jt}\}$, where j index municipalities and t census waves. We estimate:

$$Y_{jt} = \psi_t + \psi_j + \beta_1 \times \ln homrate_{jt} + \beta_2 \times wage_{jt} + \epsilon_{jt} \tag{1}$$

Violence affects migration both by decreasing immigration and increasing out migration, although the relative strength of these effects varies by subgroup. A one percentage point

Table 1: Summary statistics, by migration period

	(1) 1995 to 2000 mean/sd	(2) 2005 to 2010 mean/sd	(3) 2010 to 2015 mean/sd
Homicide rate per 100k, avg over period	12.55	13.95	20.50
	19.33	24.21	35.57
Total homicides per year	10859.28	14315.22	23881.15
Internal migrants, thousands	5644.82	6659.55	6390.56
Observations	2468	2468	2468

Notes. This table shows summary statistics for the main variables used in our empirical exercises. Standard deviations for each variable reported below it.

increase in the local homicide rate is related to a noisy .015% increase in total outflows and a significant .03% decrease in total inflows. This corresponds to the broad pattern suggested by the binscatters, where inflows respond to violence but outflows do not.

4.1 Predicted route conflict

Violence is unlikely to be exogenous in the migration equation. If some unobserved municipal characteristics correlate with violence and migration, or if migration causes violence, then OLS estimates are biased. There is some evidence of the former: Dell, Feigenberg, and Teshima 2018 find that violence increased more where local labor markets were depressed. They argue that weak local labor demand makes it easier for cartels to hire. While we control for labor market conditions using wages, this is likely to be an incomplete measure. The unobserved quality of local institutions, such as police or courts, can also affect migration rates and violence. An instrumental variable is then needed to estimate the effect of violence on migration.

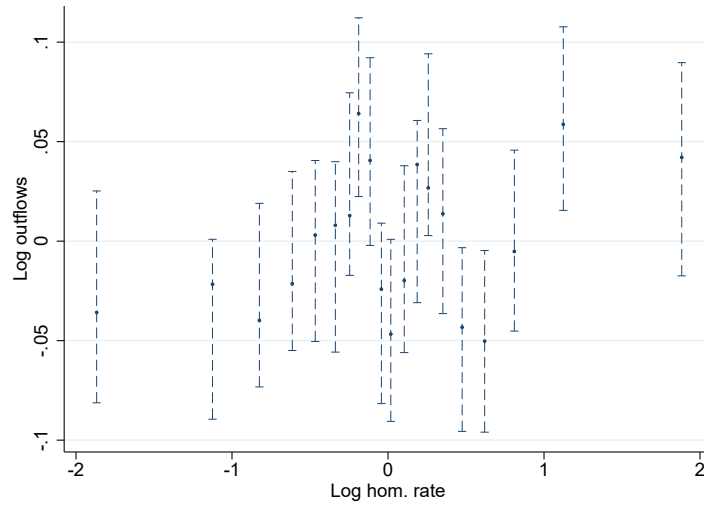We construct our instrument for violence by modelling the location of cartel conflict over

Figure 3: Homicide rate and Migration

(a) Homicide rate and inflows
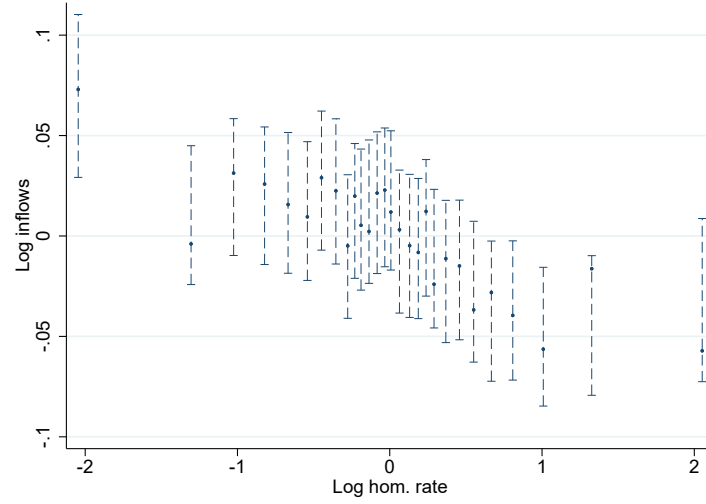
(b) Homicide rate and outflows

Notes. This figure shows binscatter plots of inflows and outflows against the log homicide rate controlling for time and municipality fixed effects and local wages, following Cattaneo et al. 2019.

drug routes in time. If DTOs fight for traffic routes, and by doing so increase local violence, then we can capture some of the variation in violence by predicting where conflict is likely. To the extent that the location of conflict does not depend on other municipality characteristics that matter for migration, the exclusion restriction will hold.

The exact location of traffic routes and DTO conflict is unobserved, so we assemble a model to predict them. To do so, we bring together information on where drugs are produced, imported, and trafficked into the United States, the identities of the DTOs present in each of these locations, and the profile of alliances and conflicts between them over time. Next we describe its construction.

First define, for each period, an alliance as a group of DTOs documented to be collaborating in that period. Journalistic accounts (Hernández 2010), text analysis of messages left by DTOs (Laura H Atuesta and Pérez-Dávila 2018), and the National Drug Threat Assesment documents from the D.E.A. detail the formation and dissolution of alliances between DTOs, as well as conflicts. This information is summarized in Table 2. Columns correspond to cartels, and rows to periods. Allied DTOs are shown in the same color.

For a given period and alliance, we define drug origins as municipalities classified as origins based on crop destructions by the Mexican Army or ports with high drug-trafficking activity (D.E.A.) where some member of the alliance is present. Section 3 describes the origin data in more detail. We consider three types of origins, according to the kind of drug sourced: poppy seed and marihuana, grown in Mexico, and imported drugs that enter the country through ports (e.g. cocaine). For each of these origins, we model drug routes as the shortest highway route that connects that origin to a destination on the US border, *where the alliance is present*. Finally, we define conflict as a function of the number of alliances that are present in a given municipality.

We implicitly assume in our model that origins and destinations of drug trafficking routes are controlled by the same DTOs throughout the period of study. We believe this is reasonable, as DTOs defend their home turfs and access points to the US, since they are essential to their business. Most news reports mention the same DTOs in origins and destinations in time. Thus, the time variation is given by changes in routes that occur when a new alliance is formed or when it breaks down. This redefines the set of possible destination points for a given origin. Second, routes from competing DTOs might be joined into a single route if they become allies. The opposite is also true: a splintered alliance may lead to an increase in the number of routes that go through a given municipality.

Contested routes vary in time with the profile of alliances and conflict between cartels. These are caused in general by conflict and agreements between high-level members of cartels, and so we expect them to be unrelated to local municipality characteristics other than violence. Therefore, we expect our measure of predicted conflict to only affect migration through violence, meaning it satisfies the exclusion restriction.

The relevance of our instrument depends on two premises: that violence increases where cartels fight, and that they do so to control traffic routes or drug shipments. If so, municipalities on a route that DTOs fight over will experience higher levels of violence. Both premises find support in the literature. Trejo and Ley 2018 find cartel conflict changes the geographic pattern of violence over time. On the other hand, Castillo, Mejía, and Restrepo 2018 find that periods and locations where cocaine shipments are presumably more valuable see increased violence.

Define a route for drug d, $r_{a_t}^d$ starting at an origin o, where alliance a is present, as the path over federal highways that minimizes distance between o and a destination where a is present. We denote our instrumental variable Z_{jt}^d for municipality j in time t as the number of alliances

Table 2: Cartel alliances over time

2001-2002	Beltran	Gulf C.	Jalisco	Juarez	Familia	Sinaloa	Templar	Zetas
2003-2005	Beltran	Gulf C.	Jalisco	Juarez	Familia	Sinaloa	Templar	Zetas
2006	Beltran	Gulf C.	Jalisco	Juarez	Familia	Sinaloa	Templar	Zetas
2007	Beltran	Gulf C.	Jalisco	Juarez	Familia	Sinaloa	Templar	Zetas
2008-2009	Beltran	Gulf C.	Jalisco	Juarez	Familia	Sinaloa	Templar	Zetas
2010	Beltran	Gulf C.	Jalisco	Juarez	Familia	Sinaloa	Templar	Zetas
2011-2014	Beltran	Gulf C.	Jalisco	Juarez	Familia	Sinaloa	Templar	Zetas

Notes. This table summarizes the formation and dissolution of alliances between cartels. Columns correspond to cartels and rows to periods. Allied cartels are shown in the same color.

with drug d routes that pass through j at time t.[9]

$$Z_{jt}^d = \sum_{\tau=t-5}^{t} \sum_a \mathbb{1}(\text{j is 40 km or less from } r_{a\tau}^d)$$

Figure 4 shows the predicted network of routes of alliance 1 and 2, and the logarithm of the homicide rate. From this picture, we see that some of the most violent municipalities in the country lie within a close distance of contested routes –routes used by both alliances. The routes we use to construct the instrument are modelled and not observed, so we are likely to miss some important variation. In particular, we cannot account for change in routes due to conflict. However, it is likely that the most direct routes we model will be attractive for DTOs and therefore generate conflict when contested.

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[9]Since cartels enter and exit alliances at times that do not match our migration periods, we calculate routes by cartel alliance periods and aggregate them.

Figure 4: Poppy seed routes in 2015 and the homicide rate
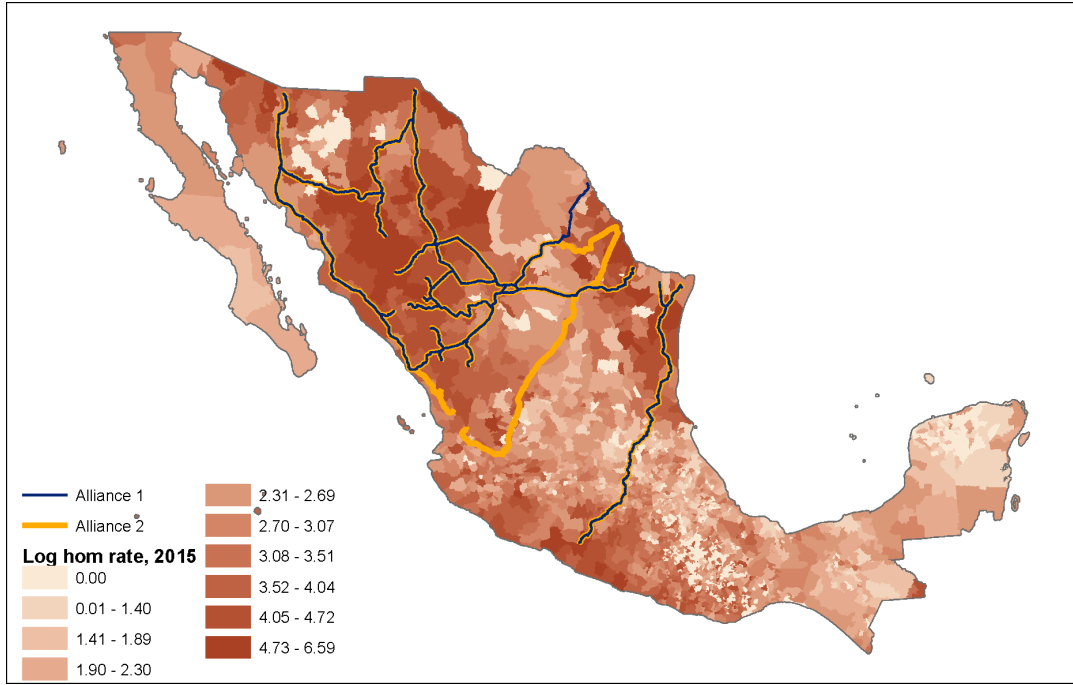
Notes. Figure 4 shows the predicted network of routes operated by alliance 1 and 2, and the logarithm of the homicides rate.

We reestimate (1) using instrumental variables to estimate the causal effect of the homicide rate on migration. The identification condition in this equation is that being on a route after the start of the militarization of narcotic law enforcement in 2006 affects migration only through violence, conditional on the controls.

While this assumption is untestable, we can check whether route and non-route locations behave differently before and after the start of the War on Drugs. Figures 5a and 5b show estimates of the interactions of period dummies and above-median conflict municipality dummies, considering only the port (cocaine) instrument. Municipalities that would be high and low

conflict in 2010 and 2015 are similar in 2000, before violence increases, both in terms of outflows and inflows. In the next periods, high conflict municipalities in each year seem to have higher outflows and lower inflows in those years. These two facts together support that the start of the War on Drugs changed the relative attractiveness of drug route municipalities and non drug route ones, mainly through the effect of violence. This is the variation behind the IV estimates in Table 4.

Figure 5: Migration on route and non-route locations

(a) Outflows
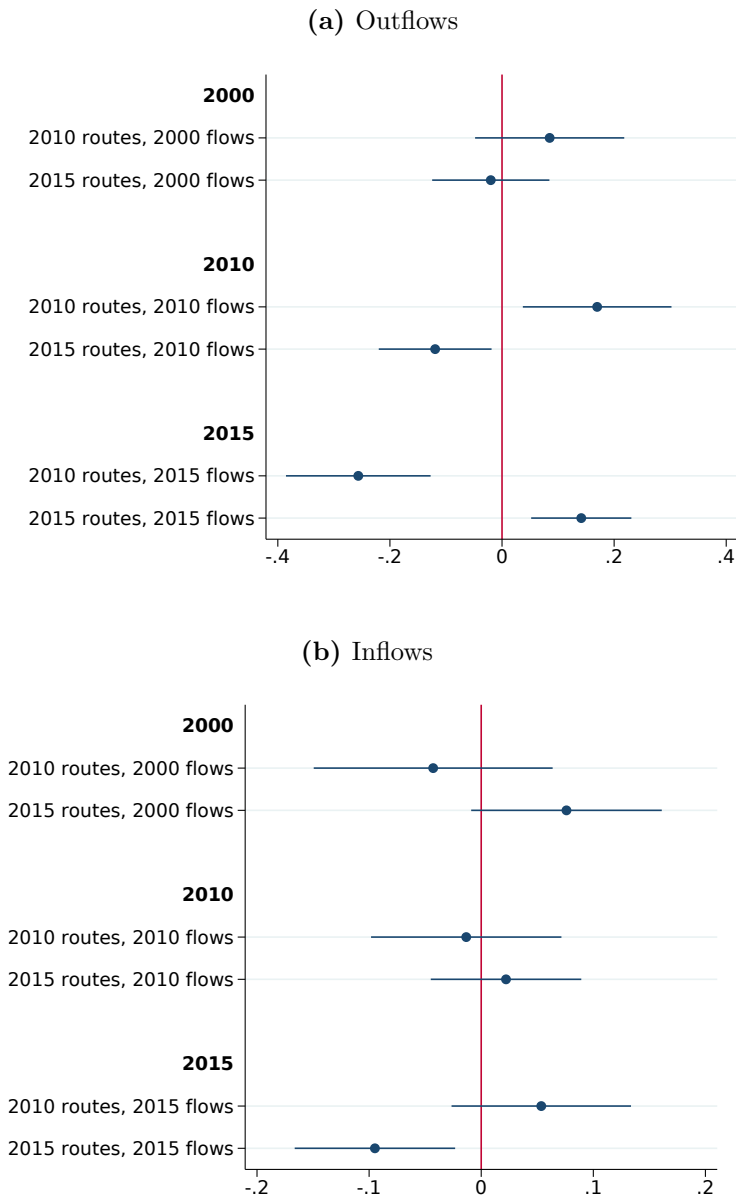
(b) Inflows

Notes. This figure shows panel regression coefficients of the logarithm of outflows (a) or the logarithm of inflows (b) on year route interactions. The regressions include municipality and year fixed effects. Standard errors are clustered at the municipality level.

The IV estimates tell a similar story to the OLS ones, but show much stronger effects. Violence affects migration mainly through decreased inflows. An increase of 1% in log homicide rate implies a .21% decrease in total inflows. The effect on the low skilled is even larger, at .27%

Again, outflows are mostly unaffected, except for the skilled –who we take to have generally low migration costs. This effect is mitigated by increased inflows into violent locations, although of a smaller magnitude. Our results imply a net skilled net migration decrease of .12%.

Since IV estimates are larger than OLS ones, we conclude that violence assigned at random has a larger effect on migration than equilibrium assigned violence.

Overall, the results point to individuals disliking to live in violent places –but finding that moving costs are large relative to the disutility imposed by local violence. Violence, however, does make these municipalities less attractive for potential newcomers. Overall, these reduced form estimates show the increase in the homicide rate affected internal migration patterns, and suggest a role for moving costs.

The unskilled seem more likely to not migrate into a violent location than the skilled. This is consistent with a result from previous literature (Ajzenman, Galiani, and Seira 2015) showing lower income individuals are most affected by local violence.

There remain important questions that cannot be answered without a model. First is the total number of migrants caused by violence. Absent violence, different municipalities would attract and repel migration. Since relative characteristics of locations determine the distribution of population, no reduced form exercise can answer this question.

Second is welfare. Even if we knew the precise number of individuals displaced by violence, this number would not tell the whole story about the welfare consequences of the increase in violence. This overall cost depends on how much individuals dislike living in violent locations,

on migration costs, the geographical pattern of migration, and how much local labor and land markets respond to changes in population. A large amount of internal migration is consistent with low welfare costs if migration is not costly, and markets at destinations can easily accommodate the incoming population. On the other hand, low levels of internal migration are consistent with high welfare costs if migration is costly and violence is a large disamenity. In section 3, we set up a model to answer these questions quantitatively.

Table 3: First Stage

	Log Violence
Poppy route	0.017***
	(0.004)
Marihuana route	0.042***
	(0.006)
Cocaine route	0.025**
	(0.008)
Observations	7037

Notes. Standard errors clustered at the municipality level are reported in parentheses.* Significant at 5%. ** Significant at 1%.*** Significant at 0.1%. SW F-statistic is 62.1

Table 4: Reduced form coefficients, migration and violence

Log Outflows			
	All	Unskilled	Skilled
OLS: Log homicide rate	0.015	0.023	-0.014
	(0.013)	(0.012)	(0.008)
IV: Log homicide rate	-0.074	-0.033	0.249***
	(0.047)	(0.046)	(0.065)
Observations	7037	7037	7037
Log Inflows			
	All	Unskilled	Skilled
OLS: Log homicide rate	-0.030***	-0.040***	0.007
	(0.007)	(0.011)	(0.009)
IV: Log homicide rate	-0.211***	-0.271***	0.180**
	(0.035)	(0.039)	(0.067)
Observations	7037	7037	7037

Notes. Standard errors clustered at the municipality level are in parentheses. We reject that the equation is underidentified and instruments are weak. First stage F stat is ≈ 60. * Significant at 5%. ** Significant at 1%. *** Significant at 0.1%.

5 Model and Estimation

This section presents our model and estimation strategy to study the effects of drug violence on the spatial distribution of people in Mexico. We follow the spatial equilibrium models of Moretti 2011 and Diamond 2016 closely. In them, a local amenity decrease in municipality j (such as higher violence) has consequences through several channels. Marginal workers move and pay the moving cost. Inframarginal workers live with the decreased amenity, and, if prices respond to local population, with higher wages, and lower rents. The overall effects depend on the relative sizes of the preference parameters that govern the migration choice, as well as the elasticities of prices to local changes in population. In subsection 5.1, we estimate a discrete choice model to quantify labor supply as a function of local characteristics. In 5.2 we estimate the elasticity of labor demand. Rent elasticity is harder to estimate due to data constraints, and thus, we only present some preliminary results in that respect.

5.1 Labor Supply

We write labor supply using a simple discrete choice model. It will constitute the central piece of the preference parameter estimation. Labor supply at municipality j at time t depends on individuals' utility of living in a given city. Let V_{ijt} be individual i's value function when choosing to live in j at time t. Define $viol_{jt}$ as municipality level violence, w_{jt} as local wages, and $move_{ijt}$ as an indicator equal to 1 if i needs to move to live in j, and zero otherwise. ϵ_{ijt} is an individual preference shock, distributed Type 1 Extreme Value. ξ_{jt} are unobserved, time varying city characteristics that affect all individuals' location choices.

$$V_{ijt} = \beta_v viol_{jt} + \beta_w w_{jt} + \gamma_j + \xi_{jt} + \beta_c move_{ijt} + \epsilon_{ijt} \tag{2}$$

This value function depends on i through the individual shock and the location at the beginning of the period, which we take as exogenous.

Define

$$\delta_{jt} = \beta_v viol_{jt} + \beta_w w_{jt} + \gamma_j + \xi_{jt} \tag{3}$$

Then

$$V_{ijt} = \delta_{jt} + \beta_c move_{ijt} + \epsilon_{ijt} \tag{4}$$

Equation (5.1.2) implies that the share of i's origin population that moves to j in t is

$$S_{ij} = \frac{\exp\left(\delta_{jt} + \beta_c move_{ij}\right)}{\sum_l \exp\left(\delta_l + \beta_c move_{il}\right)} \tag{5}$$

We can estimate δ_{jt} and β_c using maximum likelihood for $t = 2000, 2010, 2015$. This amounts to choosing the estimates of δ_{jt} and β_c that make the model match the share of individuals observed to live in each j and the share of movers.

5.1.1 Labor Supply: IV Estimation

We want to estimate the preference parameters associated with specific location characteristics. We proceed using a two step estimator similar to the one used in Diamond 2016. With estimates for δ_{jt} in hand, we can estimate equation 3 using IV. Instrumental variables are necessary here because we know that unobserved local characteristics ξ_{jt} will change with violence. Local home values and rents are likely to decrease, and are unobserved. Wages are likely to increase, due to the negative net migration. We are interested in estimating β_w and β_v, so we need to instrument for violence and wages.

To generate variation in local wages, we use Bartik shocks. Let $L_{l\tau}$ be national employment in

sector l at time τ, and $s_{lj\tau}$ be the share of employment in j in sector l. Define Bartik instruments B_j as

$$B_{jt} = \sum_l \left(L_{l,t} - L_{l,t-5} \right) s_{lj,t-5} \tag{6}$$

These municipality level shocks plausibly affect the desirability of a city $\delta_{j,t}$ only through the labor market, so they serve as instruments. We need a relevant instrument Y_{jt} for violence that plausibly satisfies exogeneity; something that affects average quality of life in a municipality only through violence. We again use our contested route instrument from section 2, and estimate 3 using IV.

This yields estimates for β_v and β_w, as well as values for residuals ξ_{jt}. Table 5 shows our estimates. Homicide rate decreases utility for skilled and unskilled individuals, but it's only significant for unskilled. Wages are positive and significant at 10% for unskilled workers, and not significant for skilled workers.

5.1.2   Labor Supply: Results

Willingness to pay is defined as follows. In equation , indirect utility is kept constant if $viol_{jt}$ increases by 1 if w_{jt} increases by $\frac{\beta_v}{\beta_w}$. This is the willingness to pay to avoid the unit increment in $viol_j t$, in log wage units. By analogy, the WTP to avoid moving is $\frac{\beta_c}{\beta_w}$.

Table 6 shows the results implied by the IV preference parameter estimation on willingness to pay. These correspond only to the unskilled group. Our discrete choice model procedure suggests that the welfare of unskilled workers when wages wages are 1% lower is the same as that when the homicide rate per 100 thousand decreases by 3%. Moving costs are significant: the estimation results show workers have the same utility when they move and when they stay if

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Table 5: Utility coefficients

	Unskilled	Skilled
Log homicide rate (β_v)	-0.050*	-0.031
	(0.020)	(0.063)
Log wage (β_w)	0.145	-0.207
	(0.081)	(0.129)
Observations	6999	4735

Notes. Standard errors clustered at the municipality level are reported in parentheses.* Significant at 5%. ** Significant at 1%.*** Significant at 0.1%. The first stage of this regression is reported in Table 3

Table 6: Willingness to pay for violence and moving in a municipality (thousand pesos)

$WTP_{violence}$	WTP_{moving}
-0.34	-69.27

the place they move to has 70% larger wages. These are economically important for households. The mean monthly wage over this period is 3.982, in thousand pesos (about 210 USD).

5.2 Labor Demand

Violence may also affect welfare at through changing prices, if migration flows are concentrated at some destinations and destination prices respond to population inflows. Let violent origins be those above the 90th percentile of the homicide distribution in a given year, say 2010. If migrants from those origins pick similar destinations, then inflows may be large enough to change local labor and land markets. Figure 6 shows all destinations of the 10% most violent origins as points. The horizontal axis shows the share of migrants from these violent origins, and the vertical shows share of migrants from all origins. If migrants from violent origins distributed

evenly among destinations, then we would see many points around the 45 degree line. Since we see a large mass of destinations beneath it, we conclude that migrants from violent origins disproportionately choose to live in a few cities.

We now proceed to estimate the elasticity of labor demand. Write reduced form inverse labor

Figure 6: Migration destinations from top 10% violent municipalities
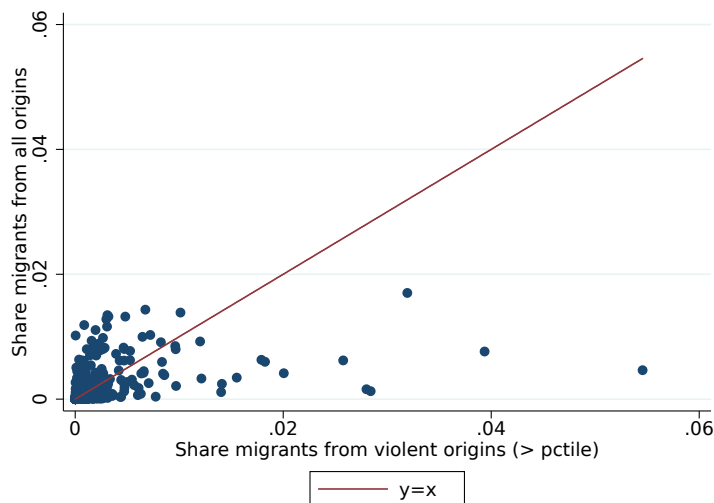
Notes. This figure shows all destinations of highly violent origins as points. The horizontal axis shows the share of migrants from violent origins, and the vertical shows the share of migrants from all origins. There are 824 municipalities under the line and account for 0.63 of all migrants from violent origins.

demand as:

$$wage_{jt} = \alpha_t + \gamma_j + \beta_w^d empl_j + X_{jt} + \xi_{jt}^d$$

In order to identify the labor demand elasticity, we need to leverage a shock to labor supply at the local level. Since we observe both origins and destinations for migration flows, we can use push factors at origins, aggregated by destination, as shocks to local labor supply. Other work uses similar strategies to identify the role of inflows on local markets. Imbert et al. 2018

and Derenoncourt 2019 study the effects of migration on destinations and use push factors at origins combined with past migration patterns as instruments for inflows. Imbert et al. 2018 uses changes in agricultural prices at origin as push factors to study productivity in China, and Derenoncourt 2019 uses war spending and shocks to cotton, tobacco, and mining to understand the effect of black immigration on US cities.

We follow Derenoncourt 2019 closely and take an agnostic approach to predict outflows. We use LASSO, a penalized regression technique, to find predictors of outflows at the municipality level. In particular, let $F_{jj'}$ be the likelihood that a person will migrate from j to j' conditional on leaving j and $\hat{outflows}_j$ the predicted out migration based on characteristics of municipality j. In our data, we can define a labor supply shock at destination municipality j', using migration shares in 2000,

$$B_{j'}^s = \sum_j F_{jj'} \times \hat{outflows}_j \tag{7}$$

$\hat{outflows}_j$ is constructed from a LASSO regression at the municipality level of $outflows$ on the following set of regressors: nr. of private homes in a municipality, nr. of unoccupied private homes, total housing, sector shares from the Economic Census, historic support for PAN party[10], destruction of marijuana and poppy crops, a dummy for maritime ports with high DTO presence, income of those employed, unemployment rates (both, separately for high and low SES), latitude and longitude, historic homicide rates by year, informal labor, nr. of paid and unpaid employees, employees with no base salary, nr. administrative personnel, nr. of outsourced employees, nr. of cartels with presence in the municipality, distance to the nearest drug trafficking route (as

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[10]The PAN party held the presidency between 2000 and 2012. Dell 2015 has argued that municipalities where PAN ruled were more likely to ask for and receive federal assistance to enforce anti-narcotic laws.

well as distance to the nearest route controlled by a specific DTO), rents in 2000, and extortion figures at the state level.

We estimate this regression separately for 2010 and 2015. We express out migration and other variables in per capita terms when appropriate. In 2010 our model selects paid employees, outsourced employees, informal labor, total housing, as well as 5 sector shares variables. In 2015, the model keeps unoccupied housing, latitude, paid employees, administrative employees, unpaid employees, informal labor, number of cartels, total housing and extortion, as well as 7 sector share variables.

Our instrument predicts the flow of migrants into a location, so we us it to instrument for changes in labor. Taking first differences in the labor demand equation, we get:

$$\Delta wage_{jt} = \Delta \alpha_t + \beta_w^d \Delta empl_j + \Delta X_{jt} + \Delta \xi_{jt}^d$$

We estimate this equation using 2SLS with $B_{j'}^s$ as an instrument for $\Delta empl_j$, on the sample of all municipalities for $t = 2010, 2015$.

Table 7: IV estimates of wage elasticity

	Δ log wage
Δ employment	-0.895
	(1.391)
Observations	4552
SWF	0.488
SWFp	0.485

Notes. Standard errors are in parentheses. Municipality level regression. Dependent variable is change in monthly wages from 2000 to 2015. * Significant at 5%. ** Significant at 1%. *** Significant at 0.1%.

Table 7 shows results for the IV estimation. Destination wages seem to be relatively inelastic

to population inflows, pointing to low general equilibrium effects of violence through its effect on migration.

We also would like to consider the effect of housing markets on welfare. If housing prices respond to population inflows, then violence might decrease welfare even in nonviolent locations. Unfortunately, rent data is not available in the census, so we estimate rent elasticity in a cross-section of municipalities in the appendix. We estimate an elasticity of 2.4 of rents with respect to population. While we estimate a large elasticity, high ownership rates and shallow rental markets in our setting lead us to disregard this channel, especially in light of the small magnitude of general equilibrium effects we find later.

6 Counterfactuals and Welfare

The estimated model lets us study the role moving costs and general equilibrium effects play in determining the effects of violence. We calculate the welfare effect of increased homicide rates under different assumptions about the quantities and prices that adjust. In particular, we compare the model with observed violence to one with counterfactual low violence when moving costs are infinite, zero, and the estimated value $\hat{\beta}_c$ in partial equilibrium, and finally in general equilibrium. In all the exercises that follow, counterfactual homicide rates are equal to the minimum of 2000 and 2010 levels.

We classify individuals according to their observed and counterfactual destinations, and study each group separately. This allows us to quantify welfare for marginal and inframarginal individuals, highlighting the role of mobility. In addition, this classification allows us to study the displaced population. In what follows, we say an individual is displaced if they move from their places of origin due to the increase in violence. The number displaced is often used as an informal summary statistic of the social cost of conflict (see, e.g. UN Office for the Coordination of Humanitarian Affairs, 2016). Perhaps for this same reason, academics in other social sciences, Mexican authorities, and human rights organizations have shown substantial interest in estimating the number of Mexicans displaced by the increase in homicides (Díaz Pérez and Romo Viramontes 2019, Pérez Vázquez et al. 2019, Rubio Díaz-Leal 2014, IDMC 2012). Our study highlights that under high moving costs, this number may be misleading about the total welfare cost of conflict.

Our model provides a transparent estimate of the number displaced, based on individual migration choices. Existing estimates of displacement rely on survey questionnaires. Several national surveys include a question about some measure of internal migration and its cause

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(see Díaz Pérez and Romo Viramontes 2019 for a detailed survey). Migration may have many simultaneous causes, so self-reported answers may be unreliable.

In addition to the displaced, we study inframarginal stayers, inframarginal movers, and other marginal movers. Inframarginal individuals do not change their choices when faced with higher violence. If their destination and origin municipalities are the same, they are stayers - otherwise they are movers.

We say a municipality of origin is violent when its homicide rate increased between 2000 and 2010. The last group includes the two remaining cases: movers whose destination changes in the counterfactual, and marginal movers from nonviolent origins. We report welfare separately for each of our demographic groups. The following defines the groups and welfare measures precisely.

For each origin i and destination j, define welfare as a function of origin, destination, violence v, and moving costs β_c as follows. We study only a single period (2010) and group (unskilled), so we do away with those sub-indices. Recall that $\hat{\beta}_v$, $\hat{\beta}_w$, $\hat{\beta}_c$, $\hat{\gamma}_j$ and $\hat{\xi}_{j,2010}$ are our estimates of utility parameters, and that w_j is log wages. $move_{ij}$ is a dummy equal to one if $i \neq j$. Define

$$W(i, j, v, \beta_c) = \frac{\hat{\beta}_v v_j + \hat{\beta}_w w_j + \hat{\gamma}_j + \hat{\xi}_{j,2010} + \beta_c move_{ij}}{\hat{\beta}_w} \tag{8}$$

W_{ij} is the mean utility of a person originating from i and moving to j in log wage units.

Let o and c index observed and counterfactual choices. Welfare effects from violence depend on individuals' origins, observed destinations, and counterfactual destinations. The following defines the welfare change of an individual originating from i, who chooses j^o under observed violence and j^c in a safer counterfactual. It is the difference in utility measured in log wages

and multiplied by nominal mean wage to obtain a measure in pesos.

$$\Delta W(i, j^o, j^c, v^o, v^c, \beta_c) = \overline{wage}_{2010} \left(W(i, j^o, v^o, \beta_c) - W(i, j^c, v^c, \beta_c) \right) \tag{9}$$

The number of people who experience welfare change $\Delta W(i, j^o, j^c, v^o, v^c, \beta_c)$ is

$$\mu(i, j^o, j^c, \beta_c) = P_i \times S(i, j^o, v^o) \times S(i, j^c, v^c) \tag{10}$$

where $S(i, j, v)$ is the share of people from i who choose j under violence vector v, and P_i is the original population of i. This follows from the independent individual level shocks across counterfactual and observed states of the world. The total welfare effect of increased violence is

$$\sum_i \sum_{j^o} \sum_{j^c} \mu(i, j^o, j^c, \beta_c) \times \Delta W(i, j^o, j^c, v^o, v^c, \beta_c) \tag{11}$$

Adding the values of μ over different sets of i, j^o, and j^c gives us the number of inframarginal stayers and movers, displaced, and other marginal movers. An individual with $j^o = j^c$ is inframarginal, in that their location decision is the same in the observed and counterfactual versions of the world. If a person is inframarginal and $i = j^c$, then we say she is an inframarginal stayer (IS). If not, she is an inframarginal mover (IM)- they move away from their origin to the same destination under both violence levels. On the other hand, if $j^o \neq j^c$ then violence changes the person's migration choice -i.e. they are marginal. We divide marginal movers into displaced and other marginal. First, we call a person displaced (D) if they move away from their origin i only when it turns violent. This means that $i = j^c \neq j^o$, and violence increased in i between

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2000 and 2010.[11] Second, we group the rest of the marginal movers (other marginal, OM): those who decided not to move because their preferred destinations became violent, or who move in both states, but to different destinations, or whose origins are not violent.

Population and welfare for each group is:

$$\Delta IS(v_j^c, w_j^c, \beta_c) = \sum_{j^o} \sum_{j^c=j^o} \sum_{i=j^c} \Delta W(i, j^o, j^c, \beta_c) \mu(i, j^o, j^c, \beta_c) \tag{12}$$

$$\Delta IM(v_j^c, w_j^c, \beta_c) = \sum_{j^o} \sum_{j^c=j^o} \sum_{i\neq j^c} \Delta W(i, j^o, j^c, \beta_c) \mu(i, j^o, j^c, \beta_c) \tag{13}$$

$$\Delta D(v_{jt}^c, w_j^c, \beta_c) = \sum_{j^o} \sum_{j^c!=j^o} \sum_{i\neq j^o, i\in V, i=j^c} \Delta W(i, j^o, j^c, \beta_c) \mu(i, j^o, j^c, \beta_c) \tag{14}$$

$$\Delta OM(v_{jt}^c, w_j^c, \beta_c) = \sum_{j^o} \sum_{j^c!=j^o} \sum_{i=j^o\cup i\notin V\cup i\neq j^c} \Delta W(i, j^o, j^c, \beta_c) \mu(i, j^o, j^c, \beta_c) \tag{15}$$

Having described how we measure welfare, we now lay out our counterfactual exercises and what we learn from each. These exercises vary in two dimensions: moving costs and whether prices at destinations adjust or not. First, we set the cost of moving high enough so that no one moves. By allowing no margins of adjustment, this is the counterfactual with maximum welfare cost. Second, we fix moving costs to their estimated value. The difference in welfare between this and the previous counterfactual quantifies how migration lets individuals substitute away from conflict in the estimated model. Third, we allow for wages at destinations to respond to local employment changes, under estimated migration costs. The difference between this and the partial equilibrium case quantifies the effect of price adjustments. Last, we calculate the

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[11]This definition compares counterfactuals where the same individual receives independent shocks. For this reason, even two counterfactuals with the same violence levels will have some displaced individuals - some will get high values from moving out in one counterfactual and high values of staying in another, even if indirect utility of choices is the same.

Table 8: Population effect of violence increase, in thousands

Counterfactual	Infr. Stayers	Infr. Movers	Marg. Displaced	Other Marg.
$\beta_{move} = \infty$, PE	91444.27	0.00	0.00	0.00
$\beta_{move} = \hat{\beta}_c$, PE	80567.12	1.38	2450.46	8425.31
$\beta_{move} = 0, PE$	0.64	207.81	71.09	91164.74
$\beta_{move} = \hat{\beta}_c, GE$	80569.61	1.38	2449.46	8423.82

Notes. This table shows the number in each population class implied by the observed increase in violence, under infinite, estimated, and zero moving costs in partial equilibrium, and estimated costs in general equilibrium.

effects under perfect mobility in partial equilibrium. Here, individuals can adjust their location at no cost without wages decreasing at destinations, so it serves as a lower bound on the cost of violence. Table 8 and 9 show the population effect and welfare effect of violence under these different assumptions.

In the counterfactual with no moving, everyone is inframarginal and no one changes location. In this case, the total welfare cost is 195 billion pesos. Mexico's GDP in 2010 was around 13 trillion pesos, so these costs amount to 1.4 percent of GDP per year. This is the upper bound to the welfare loss from violence in 2010, as there are no margins for individuals to adjust.[12]

The second counterfactual shows the effect of increased violence under estimated moving costs. We estimate 2.4 million displaced, and 8.4 million other marginal individuals. The number displaced is low relative to the total number of marginal movers. The effect of violence on the distribution of population then mostly worked through distorted migration decisions other than displacement. This is consistent with what we find in section 4, where we found the first order effects of violence through changes in immigration flows. The total welfare effect on marginal individuals is on the order of 3 billion pesos.[13] Inframarginal stayers account for most

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[12]For this reason, general equilibrium effects are irrelevant.

[13]While welfare for the displaced drops dramatically, this is offset almost completely by a welfare *increase* to

Table 9: Welfare effect of violence increase, in million pesos

Counterfactual	Infr. Stayers	Infr. Movers	Marg. Displaced	Other Marg.	Total
$\beta_{move} = \infty$, PE	-195163.41	0.00	0.00	0.00	-195163.41
$\beta_{move} = \hat{\beta}_c$, PE	-162820.59	-3.45	-3758093.62	3753017.23	-167900.43
$\beta_{move} = 0, PE$	-1.09	-519.63	-14361.17	-126833.81	-141715.69
$\beta_{move} = \hat{\beta}_c, GE$	-163491.86	-3.34	-3755725.16	3746724.75	-172495.61

Notes. This table shows the change in each population class implied by the observed increase in violence, under infinite, estimated, and zero moving costs in partial equilibrium, and estimated costs in general equilibrium.

of the welfare decrease. At estimated moving costs, the welfare cost of violence is 167 billion pesos, or 1.3% of GDP per year. This is 86% of the maximum cost. Moving costs are large enough so that the estimated cost is very close to the upper bound. This finding is consistent with other work studying spatial equilibrium in developing countries, which finds large welfare gaps across locations (Gollin, Kirchberger, and Lagakos 2017a and Chauvin et al. 2016). Social relationships, networks, and transport infrastructure in less developed countries may make it more costly for individuals to relocate. For this reason, advantageous moves may not happen.

Third, when we allow wages at destinations to respond to population changes, welfare losses increase to 172 billion pesos, or 88% of the upper bound. Since moving costs are high, and population changes from violence are small, price adjustments have small aggregate effects on population and welfare.

other marginal movers. Again, this is due to the independent counterfactuals - welfare for some individuals is larger when violence increases, since their individual shocks lead them to move only in the peaceful counterfactual.

Finally, the last counterfactual shows the welfare effect of violence under no moving costs. While total welfare loss is 25% smaller than the baseline case with no mobility, they still amount to $\approx 1\%$ of GDP per year. This is because many individuals still move, for idiosyncratic reasons, to locations that become violent. Since these individual shocks are important for choices even when violence is high, costs are still large.

7 Conclusions

We find net migration away from high homicide rate locations, implying the homicide rate is a disamenity. This is driven by effects on inflows and not outflows, pointing to important moving costs. The structural labor supply model shows that unskilled workers are willing to accept a 1% wage reduction to decrease local homicide rates by 3%. Counterfactuals show that large moving costs mute the migration response, but inframarginal stayers account for most of the welfare losses. Further, large moving costs are a root cause of high welfare costs of violence. With infinite moving costs, welfare losses would only be 16% larger than under estimated moving costs. Our instrumental variable estimations point to elastic labor markets. We find evidence of concentrated migration to some destinations, but small GE effects.

High moving costs prove to be important in explaining the welfare effect of violence in a developing country context. For this reason, our results show displacement offers only a partial summary of the social cost of the violence caused by organized crime.

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A   Housing Supply

In order to evaluate welfare, in principle we also need to know how elastic the supply of housing is. If housing supply is inelastic, then population inflows due to violence might decrease welfare even in nonviolent locations.

Rent data is not available in the census, so we are forced to estimate the rent elasticity in a cross-section of municipalities. Letting j index municipalities, R_j be monthly rent, N_j be employment at j, $pop_{2005,j}$ be population in 2005, and B_j the population employment supply

shock detailed above, we estimate the following equation using IV.

$$\log(R_j) = \alpha + \beta_s^r + \log(N_j) + \beta X_j + \epsilon_j \tag{16}$$

Define reduced form housing supply as follows, assuming each individual consumes the same amount of housing

$$rent_j = \alpha^h + \beta^h empl_j + \xi_t^h$$

We estimate this equation using 2SLS, instrumenting for levels this time with $B_{j'}^s$ on the cross section of municipalities for which we observe rent in the expenditure survey.

Table 12 shows results from the IV estimation. Rents at destinations also seem to be elastic to population inflows. We conclude that violence may affect both land and labor prices through its effect on population changes.

Table 12: IV estimates of rent elasticity

Log employment	1.386***
	(0.00490)
Observations	29523047
SWF	2.1e+05
SWFp	0.00

Standard errors in parentheses
Dependent variable is log monthly rent, controlling for home characteristics, local population, and local log homicide rate
Model uses log hom. rate as push variable to construct the instrument
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes. Standard errors are in parentheses. Dependent variable is the logarithm of the monthly rent, controlling for home characteristics. First model uses homicide rate as push variable to construct the instrument. Second model uses the logarithm of homicide rate as push variable to construct the instrument. Significant at 5%. ** Significant at 1%. *** Significant at 0.1%.*