Trafficking Networks and the Mexican Drug War*

Melissa Dell

October, 2012

Abstract: Drug trade-related violence has escalated dramatically in Mexico during the past five years, claiming over 40,000 lives. This study examines how drug traffickers' economic objectives influence the direct and spillover effects of Mexican policy towards the drug trade. By exploiting variation from close mayoral elections and a network model of drug trafficking, the study develops three sets of results. First, regression discontinuity estimates show that drug trade-related violence in a municipality increases substantially after the close election of a mayor from the conservative National Action Party (PAN), which has spearheaded the war on drug trafficking. This violence consists primarily of individuals involved in the drug trade killing each other. The empirical evidence suggests that the violence reflects rival traffickers' attempts to wrest control of territories after crackdowns initiated by PAN mayors have challenged the incumbent criminals. Second, the study predicts the diversion of drug traffic following close PAN victories by estimating a model of equilibrium routes for trafficking drugs across the Mexican road network to the U.S. When drug traffic is diverted to other municipalities, drug trade-related violence in these municipalities increases. Finally, the study uses the trafficking model and estimated spillover effects to examine the allocation of law enforcement resources. Overall, the results demonstrate how traffickers' economic objectives and constraints imposed by the routes network affect the policy outcomes of the Mexican Drug War.

Keywords: Drug trafficking, networks, violence.

*I am grateful to Daron Acemoglu and Ben Olken for their extensive feedback on this project. I also thank Arturo Aguilar, Abhijit Banerjee, Dave Donaldson, Esther Duflo, Ray Fisman, Rachel Glennerster, Gordon Hanson, Austin Huang, Panle Jia, Chappell Lawson, Nick Ryan, Andreas Schulz, Jake Shapiro, and seminar participants at Bocconi University, the Brown University Networks conference, Chicago Booth, CIDE, Colegio de Mexico, Harvard, the Inter-American Development Bank, ITAM, the Mexican Security in Comparative Perspective conference (Stanford), MIT, NEUDC, Princeton, Stanford, UC San Diego, University of British Columbia, University of Chicago, University of Leicester, University of Maryland, US Customs and Border Patrol, the World Bank, and Yale for extremely helpful comments and suggestions.
Contact email: melissadell@fas.harvard.edu.

1 Introduction

Drug trade-related violence has escalated dramatically in Mexico since 2007, claiming over 50,000 lives and raising concerns about the capacity of the Mexican state to monopolize violence. Recent years have also witnessed large scale efforts to combat drug trafficking, spearheaded by Mexico's conservative National Action Party (PAN). While drug traffickers are economic actors with clear profit maximization motives, there is little empirical evidence on how traffickers' economic objectives have influenced the effects of Mexican policy towards the drug trade. More generally, it remains controversial whether state policies have caused the marked increase in violence, or whether violence would have risen substantially in any case (Guerrero, 2011; Rios, 2011a; Shirk, 2011). This study uses variation from close mayoral elections and a network model of drug trafficking to examine the direct and spillover effects of crackdowns on drug trafficking.

Mexico is the largest supplier to the U.S. illicit drug market (U.N. World Drug Report, 2011). While Mexican drug traffickers engage in a wide variety of illicit activities - including domestic drug sales, protection rackets, kidnapping, human smuggling, prostitution, oil and fuel theft, money laundering, weapons trafficking, and auto theft - the largest share of their revenues derives from trafficking drugs from Mexico to the U.S. (Guerrero, 2011, p. 10). Official data described later in this paper document that in 2008, drug trafficking organizations maintained operations in two thirds of Mexico's municipalities and illicit drugs were cultivated in 14% of municipalities.

This study begins by specifying a network model of drug trafficking in which traffickers' objective is to minimize the costs incurred in trafficking drugs from producing municipalities in Mexico across the Mexican road network to the United States. This model is used as an empirical tool for analyzing the direct and spillover effects of local policy towards the drug trade. In the simplest version of the model, the cost of traversing each edge in the road network is proportional to the physical length of the edge, and hence traffickers take the shortest route to the nearest U.S. point of entry. After examining the relationships in the data using this shortest paths model, the study specifies and estimates a richer version of the model that imposes congestion costs when trafficking routes coincide.

A challenge of identifying the effects of crackdowns on violence is that the state does not randomly decide to combat drug trafficking in some places but not others, and they may choose to crack down in municipalities where violence is expected to increase. In order to isolate plausibly exogenous variation in policy towards the drug trade, I exploit the outcomes of close mayoral elections involving the PAN party.[1] The PAN's role in spearheading the

[1]See Lee, Moretti, and Butler (2004) for a pioneering example of a regression discontinuity design ex-

war on drug trafficking, as well as qualitative evidence that PAN mayors have contributed to these efforts, motivate this empirical strategy. While municipalities where PAN candidates win by a wide margin are likely to be different from municipalities where they lose, when we focus on close elections it becomes plausible that the outcomes are driven by idiosyncratic factors that do not themselves affect violence. In fact, the outcomes of close elections are uncorrelated with a large number of municipal characteristics measured prior to the elections.

The network model, variation from close mayoral elections, and data on drug trade-related outcomes between 2007 and 2009 are used to examine three sets of questions. First, the study asks whether the outcomes of close mayoral elections involving the PAN affect drug trade-related violence in the municipalities experiencing these elections. It also examines the economic mechanisms that mediate this relationship. Second, the study tests whether trafficking routes are diverted to other municipalities following close PAN victories and examines whether the diversion of drug traffic is accompanied by violence spillovers. Finally, it discusses policy applications and uses the trafficking model to examine the allocation of law enforcement resources.

Regression discontinuity (RD) estimates exploiting the outcomes of close elections show that the probability that a drug trade-related homicide occurs in a municipality in a given month is 8.4 percentage points higher after a PAN mayor takes office than after a non-PAN mayor takes office. This is a large effect, given that six percent of municipality-months in the sample experienced a drug trade-related homicide. The violence response to close PAN victories consists primarily of individuals involved in the drug trade killing each other. Analysis using information on the industrial organization of trafficking suggests that the violence reflects rival traffickers' attempts to wrest control of territories after crackdowns initiated by PAN mayors have challenged the incumbent criminals.

These results support qualitative and descriptive studies, such as the well-known work by Eduardo Guerrero (2011), which argue that Mexican government policy has been the primary cause of the large increase in violence in recent years. In municipalities with a close PAN loss, violence declines slightly in the six months following the inauguration of new authorities as compared to the six months prior to the election. In municipalities with a narrowly elected PAN mayor, violence - previously at the same average level as in municipalities where the PAN barely lost - increases sharply. The results also relate to work by Josh Angrist and Adriana Kugler (2008) documenting that exogenous increases in coca

ploiting close elections. A number of studies have used discontinuous changes in policies, in the cross-section or over time, to examine illicit behavior. These studies examine topics ranging from earnings manipulation (Bollen and Pool, 2009; Bhojraj et al., 2009) to the production of defective products (Krueger and Mas, 2004) to fixing the outcomes of sporting events (Wolfers, 2006; Duggan and Levitt, 2002) to sex-selective abortions in Taiwan (Lin et al., 2008). See Zitzewitz (2011) for a detailed review.

prices increase violence in rural districts in Colombia because combatant groups fight over the additional rents. In Mexico, crackdowns likely reduce rents from criminal activities while in effect, but by weakening the incumbent criminal group they also reduce the costs of taking control of a municipality. Controlling the municipality is likely to offer substantial rents from trafficking and a variety of other criminal activities once the crackdown subsides.

The study's second set of results examines whether close PAN victories exert spillover effects. When policy leads one location to become less conducive to illicit activities, organized crime may relocate elsewhere. For example, coca eradication policies in Bolivia and Peru during the late-1990s led cultivation to shift to Colombia, and large-scale coca eradication in Colombia in the early 2000s has since led cultivation to re-expand in Peru and Bolivia, with South American coca cultivation remaining unchanged between 1999 and 2009 (Isacson, 2010; Leech, 2000; UN Office on Drugs and Crime 1999-2009). On a local level, work by Rafael Di Tella and Ernesto Schargrodsky (2004) documents that the allocation of police officers to Jewish institutions in Buenos Aires substantially reduced auto theft in the immediate vicinity of these institutions but may also have diverted some auto theft to as close as two blocks away. While a number of studies have examined the economics of the drug trade and organized crime more generally, to the best of my knowledge this study is the first to empirically estimate spillover patterns in drug trafficking activity.[2]

I begin by showing that the simple model in which traffickers take the shortest route to the nearest U.S. point of entry robustly predicts the diversion of drug traffic following close PAN victories. Specifically, I assume that it becomes more costly to traffic drugs through a municipality after a close PAN victory. Because municipal elections happen at different times throughout the sample period, they generate month-to-month within-municipality variation in predicted trafficking routes. This variation is driven by plausibly exogenous changes in politics elsewhere in Mexico and can be compared to variation in monthly panel data on actual illicit drug confiscations and violence outcomes. This approach is illustrated in Figure 1. When the shortest paths trafficking model is used, the presence of a predicted drug trafficking route increases the value of illicit drug confiscations in a given municipality-month by around 18.5 percent. Because traffickers may care about the routes that other traffickers take, I also estimate a richer model that imposes congestion costs when routes coincide. Routes predicted by this model for the beginning of the sample period are shown in Figure 2. The richer model is similarly predictive of within-municipality changes in confiscations, with the presence of a predicted trafficking route increasing the value of illicit drug confiscations

[2]Prominent examples of studies of the economics of organized crime include Steve Levitt and Sudhir Venkatesh's analysis of the finances of a U.S. drug gang (2000), sociologist Diego Gambetta's economic analysis of the Sicilian mafia (1996), and Frederico Varese's analysis of the rise of the Russian mafia (2005).

by around 19.5 percent. Robustness and placebo checks support the validity of the approach.

When a municipality acquires a predicted trafficking route, the probability that a drug trade-related homicide occurs in a given month increases by around 1.4 percentage points, relative to a baseline probability of 4.4 percent. This relationship is similar regardless of whether the shortest paths model or model with congestion is used. When routes are predicted using the model with congestion, the violence spillovers are concentrated in municipalities where two or more routes coincide.

Finally, the study's third set of results considers policy applications and extends the trafficking model to examine the allocation of scarce law enforcement resources. I discuss how the costs of violence can be incorporated into the government's resource allocation problem and how the violent response to crackdowns may be reduced. While we would not expect there to be any easy solutions to the challenges facing Mexico, the network framework provides unique information with the potential to contribute to a more economically informed law enforcement policy.

The next section provides an overview of Mexican drug trafficking and state policies towards the drug trade, and Section 3 develops the network drug trafficking model. Section 4 tests whether the outcomes of close elections involving the PAN influence drug trade-related violence and examines economic mechanisms underlying this relationship. Section 5 documents that close PAN mayoral victories divert drug traffic elsewhere and estimates versions of the trafficking model with congestion and other costs. After showing that PAN crackdowns divert drug traffic, it tests whether they result in violence spillovers. Section 6 discusses policy applications. Finally, Section 7 offers concluding remarks.

2 Drugs and violence in Mexico

2.1 The drug trafficking industry

Mexican drug traffickers dominate the wholesale illicit drug market in the United States, earning between \$14 and \$48 billion annually.[3] According to the U.N. World Drug Report, Mexico is the largest supplier of heroin to U.S. markets and the largest foreign supplier of marijuana and methamphetamine. Official Mexican government data, obtained from confidential sources, document that fourteen percent of Mexico's municipalities regularly produce opium poppy seed (heroin) or cannabis. Moreover, 60 to 90 percent of cocaine consumed in the U.S. transits through Mexico (U.S. Drug Enforcement Agency, 2011). The U.S. market

[3]Estimates are from the U.S. State Department (2009). Estimates by U.S. Immigration and Customs Enforcement, the U.S. Drug Enforcement Agency, and the Mexican Secretaría de Seguridad Pública are broadly similar and also contain a large margin of error.

provides substantially more revenue than Mexico's domestic drug market, which is worth an estimated \$560 million annually (Secretaría de Seguridad Pública, 2010). According to the U.S. National Survey on Drug Use and Health, 14.2 percent of Americans (35.5 million people) have used illicit drugs during the past year, as contrasted to 1.4 percent of the Mexican population (1.1 million people) (Guerrero, 2011, p. 82; National Addiction Survey, 2008).

Although their primary revenues are earned in wholesale drug markets, trafficking organizations also engage in a host of illicit activities that range from protection rackets, kidnapping, human smuggling, and prostitution to oil and fuel theft, money laundering, weapons trafficking, arson, and auto theft (Guerrero, 2011, p. 10). Notably, protection rackets involving the general population have increased substantially in recent years (Rios, 2011b; Secretariado Ejecutivo del Sistema Nacional de Seguridad Pública, 2011). In a nationwide survey, Díaz-Cayeros et al. (2011) found that drug traffickers are most likely to extort the poor, with 24% to 40% of surveyed households who participate in the poverty alleviation program *Oportunidades* (*Progresa*) reporting that they had been extorted by traffickers.

At the beginning of this study's sample period in 2007, there were six major drug trafficking organizations in Mexico. Official Mexican data obtained from confidential sources document that 68 percent of Mexico's 2,456 municipalities were known to have a major drug trafficking organization or local drug gang operating within their limits in early 2008. These data also estimate that 49 percent of drug producing municipalities were controlled by a major trafficking organization, with the remaining controlled by local gangs.

The term 'cartel', used colloquially to refer to drug trafficking organizations, is a misnomer, as these organizations do not collude to reduce illicit drug production or to set the price of illicit drugs. Alliances between drug trafficking organizations have been highly unstable, and there is also considerable decentralization and conflict within trafficking organizations (Williams, 2012; Guerrero, 2011, p. 10, 106-108). Decisions about day-to-day operations are typically made by local cells, as this ensures that no single player will be able to reveal extensive information if he or she is captured by authorities. Moreover, the number of major drug trafficking organizations increased from six in 2007 to 16 by 2011, with groups splitting over leadership disputes.

The second half of the 2000s witnessed massive increases in drug trade-related violence, as well as a large-scale crackdown that the next section discusses in detail. Over 50,000 people were killed by drug trade-related violence between 2007 and 2012, and homicides increased by at least 30 percent per year during most of this period (Rios, 2011b). By 2010, violent civilian deaths per capita had reached levels that were higher than in Iraq and Afghanistan during the same period, higher than in Russia during the 1990s, and higher than in Sicily during the years following the Second World War (Williams, 2012).

According to official government data for this study's sample period (December 2006-2009), over 85 percent of the violence consisted of people involved in the drug trade killing each other. 95 percent of the victims were male, and 45 percent were under the age of thirty. The violence has been public and brutal, with bodies hung from busy overpasses and severed heads placed in public spaces (Williams, 2012). This contrasts with drug trade-related violence historically, which tended to stay behind closed doors. Public displays of brutality and activities such as kidnapping and extortion affect the general public, and 2011 public opinion surveys found that security was more likely than the economy to be chosen by Mexicans as the largest problem facing their country.

2.2 Mexico's war on drug trafficking

Combating drug trafficking has been a major priority of the Mexican federal government during the second half of the 2000s. Specifically, government efforts against the drug trade have been heavily emphasized by Mexico's President Felipe Calderón (December 2006 - 2012) of the conservative National Action Party (PAN), who made fighting organized crime the centerpiece of his administration. During his second week in office, Calderón deployed 6,500 federal troops to combat drug trade-related violence. By the close of his presidency, approximately 45,000 troops were dedicated to fighting drug trafficking.

In contrast, officials tended to take a passive stance towards the illicit drug trade historically. For much of the 20th century, Mexican politics at all levels were dominated by a single party, the PRI (Institutionalized Revolutionary Party), and there were a number of well-documented instances of drug trade-related corruption (Shannon, 1988; Chabat, 2010). While the Mexican federal government periodically cracked down on drug trafficking, these operations were limited in size and scope. The PRI's dominance began to erode during the 1990s, and the first opposition president was elected from the PAN in 2000. Today Mexico is a multi-party democracy with three major parties at the federal and local levels: the right-of-center PAN, the PRI, and the left-of-center PRD (Party of the Democratic Revolution). At the beginning of Calderón's presidency, the PAN controlled the mayorship in slightly over a third of Mexico's municipalities.

Today, the government combats the drug trade using the military as well as federal, state, and municipal police. Confiscations, high level arrests, and crop eradication are typically conducted by the federal police and military, who have the requisite training and heavy weaponry, whereas municipal police usually lack the sophistication to carry out such operations. They instead can provide local information for federal interventions, which often target specific actors for whom reliable information is available (Chabat, 2010). Municipal police are also valuable allies for trafficking organizations, as they can collect detailed information on who is passing through a given location. This information is essential for protecting criminal operations and anticipating attacks by rival traffickers and federal authorities (see for example *El Pais*, August 26 2010). Municipal police form the largest group of public servants killed by drug trade-related violence (Guerrero, 2011).

Mayors, who are elected every three years at different times in each state, name the municipal police chief and set policies regarding police conduct. Qualitative evidence indicates that PAN mayors under Calderón were more likely to request law enforcement assistance from the PAN federal government than their non-PAN counterparts and also suggests that operations involving the federal police and military have been most effective when local authorities are politically aligned with the federal government (Guerrero, 2011, p. 70).[4]

Mexican officials at all levels are barred from consecutive reelection, and those who wish to continue their careers in politics after their terms have concluded have powerful incentives to aid the policy objectives of potential patrons at higher levels of government. For PAN mayors during the sample period, this likely translated into strong incentives to support Calderón's efforts to combat the drug trade. The mayorship is a common stepping stone for pursuing a career in national politics, and in a survey of 1,400 representatives serving in Mexico's lower house of Congress, the Chamber of Deputies, between 1997 and 2006, 77% of the PAN deputies had been involved in municipal politics prior to their election to the Chamber (Langston, 2008).[5] Parties are critical to accessing national politics, as they control millions of pesos in public campaign resources. Moreover, 200 of the 500 seats in the Chamber of Deputies and 32 of the 128 seats in the Senate are selected by proportional representation (PR), with PAN party leaders selecting closed candidate lists for five 40 member Chamber districts and a single national Senate district. PR candidates do not run electoral campaigns, and if party leaders place them high enough on the closed list, they will enter the legislature (Langston, 2008; Wuhs, 2006).[6] Beyond elected offices, the federal government controls thousands of appointed posts in the federal bureaucracy that

[4]For example, while drug trade-related violence initially increased in Baja California in response to a large federal intervention, the violence has since declined, and the state is frequently showcased as a success story of federal intervention. The governor of Baja California belongs to the PAN, which is the party controlling Mexico's executive branch, and the federal intervention began under the auspices of a PAN mayor in Tijuana who was enthusiastic to cooperate with federal authorities. On the other hand, in Ciudad Juarez both the mayor and governor belong to the opposing PRI party, and conflicts and mistrust between municipal and federal police have been rampant.

[5]Municipal politics is also a common stepping stone for state-level elected office, but to the best of my knowledge no systematic data on this exist.

[6]The remaining 300 seats in the Chamber and 96 seats in the Senate are elected by single member districts (SMD). PAN candidates for the SMD Chamber seats are chosen by state conventions, which require an application process to attend, and PAN Senate candidates are selected in closed primaries (Wuhs, 2006).

former politicians also often fill, providing further motivation for politicians in the same party to support federal government policy (Langston, 2008). Additional reasons why PAN mayors would support the federal government's war on drug trafficking include the fact that authorities from the same party may cooperate more effectively, PAN authorities could be less corrupted by the drug trade, or the preferences of PAN authorities or their constituents could lead them to take a tougher stance on organized crime.[7]

Mexican efforts to combat drug trafficking during the Calderón administration have focused on arrests and confiscations, with eradication of marijuana and poppy crops falling somewhat as law enforcement resources have been diverted to respond to violence (National Drug Intelligence Center, 2010). While major judicial reforms were passed in 2008, the Mexican criminal justice system remains extremely weak. It is estimated that during the 2000s only 2% of felony crimes were prosecuted (Shirk, 2011), and traffickers have often been able to run their operations from prison. Prison fights between rival gangs in which dozens are killed have become common, and in one instance in 2010 prison guards provided arms and transport to an imprisoned Sinaloa cartel death squad and released them nightly for killing rampages (Garcia de la Garza, 2012).

Mexico's large scale crackdown on trafficking appears to have been largely unanticipated. The 2006 presidential campaign, which Calderón won by an extremely narrow margin of around half a percentage point, focused on the economy with limited mention of security issues (Aguilar and Castaneda, 2009). While presidents Ernesto Zedillo (1994-2000, PRI) and Vicente Fox (2000-2006, PAN) did implement security reforms and crackdowns (Chabat, 2010), these were on a lesser scale than during the Calderón administration. As will be discussed in more detail later, evidence suggests that prior to Calderón subnational officials had less capacity to combat drug trafficking through requesting federal assistance.

The role of the government crackdown in generating massive increases in violence has been extensively debated (see Shirk, 2011, p. 8 for a discussion of this controversy). Researchers have used qualitative and descriptive evidence to argue that the state's policies have ignited violent conflicts between traffickers (see Guerrero, 2011 for a detailed discussion). Fernando Escalante (2011) uses state level correlations to argue that homicides have been spurred by the deployment of the Mexican military and federal police, and Jos'e Merino (2011) expands Escalante's analysis by using state level data and a matching strategy to argue that Mexican

[7] I have analyzed official government data on corruption, made available by confidential sources. This data records drug trade-related corruption of mayors in 2008, as measured primarily by intercepted calls from traffickers to political officials. While the data are likely quite noisy, to my knowledge they are the best source of information on drug trade-related corruption available. Corruption was no more common in municipalities where a PAN candidate had been elected mayor by a narrow margin than in municipalities where the PAN candidate had lost by a narrow margin.

homicides in 2008-2009 would have totaled 14,000 rather than 19,000 in the absence of federal government intervention. Others have argued that violence would have risen substantially in any case as a result of the diversification of drug trafficking organizations into new criminal activities (see Rios, 2011a). Additional alternative explanations for the escalation in violence range from an increase in the U.S. price of cocaine, an increase in the availability of arms, and an increase in U.S. deportation of Mexican immigrants with a criminal record to Mexican job loss to China and cultural shifts in morality (see Williams, 2012; Hope, 2011 for a discussion). This study presents causal evidence linking crackdowns to large increases in drug trade-related violence.

3 A Network Model of Drug Trafficking

This section develops a simple model of the network structure of drug trafficking, that will serve as an empirical tool for analyzing the direct and spillover effects of local policy towards the drug trade. In this model, traffickers minimize the costs of transporting drugs from origin municipalities in Mexico across the Mexican road network to U.S. points of entry. In the version of the model developed in this section, they incur costs only from the physical distance traversed, and thus take the shortest route to the nearest U.S. point of entry. This simple shortest paths model provides an intuitive starting point for examining the patterns in the data without having to first develop extensive theoretical or empirical machinery.

The trafficking routes predicted by this model are used in Section 4 to explore the mechanisms linking close PAN victories to increases in drug trade-related violence. Section 5 then shows that the model robustly predicts the diversion of drug traffic following close PAN victories and uses the predicted routes to locate violence and economic spillover effects of PAN crackdowns. Specifically, I assume that close PAN victories increase the costs of trafficking drugs through the municipalities that experience them by a pre-specified amount. Close elections occur throughout the sample period, generating plausibly exogenous month-to-month variation in predicted trafficking routes throughout Mexico. I identify spillover effects by comparing this variation in predicted routes to panel variation in illicit drug confiscations, violence, and economic outcomes.

Assuming that trafficking costs depend only on physical distance is a considerable simplification, and in particular it does not allow for interactions between traffickers. After examining the relationships in the data using the intuitive shortest paths model, in Section 5.2 I specify and estimate a richer version of the model that includes congestion costs. I use the simulated method of moments to estimate the parameters of the congestion cost function. The model developed in this section, which assumes that congestion costs are zero, is a special case of the richer model. In practice, both versions of the model robustly predict the diversion of drug traffic following close PAN victories.

I now describe the setup of the model. Let $N = (\mathcal{V}, \mathcal{E})$ be an undirected graph representing the Mexican road network, which consists of sets $\mathcal{V}$ of vertices and $\mathcal{E}$ of edges. This network, which contains 17,453 edges, is shown in Figure 2. Traffickers transport drugs across the network from a set of origin municipalities to a set of destination municipalities. Destinations consist of U.S. points of entry via terrestrial border crossings and major Mexican ports. While drugs may also enter the United States between terrestrial border crossings, the large amount of legitimate commerce between Mexico and the United States offers ample opportunities for drug traffickers to smuggle large quantities of drugs through border crossings and ports (U.S. Drug Enforcement Agency, 2011).[8] All destinations pay the same international price for a unit of smuggled drugs. Each origin i produces a given supply of drugs and has a trafficker whose objective is to minimize the cost of trafficking these drugs to U.S. points of entry. I model trafficking decisions as made by local traffickers because, as discussed in Section 2, trafficking operations are typically decentralized. While it does not matter who makes decisions when traffickers only incur costs from distance, this will become relevant when congestion is introduced into the model later in the paper.

The model focuses on domestically produced drugs, and origins are identified from confidential Mexican government data on drug cultivation (heroin and marijuana) and major drug labs (methamphetamine). Opium poppy seed and marijuana have a long history of production in given regions with particularly suitable conditions, and thus we can be confident that the origins for domestically produced drugs are stable and accurate throughout the sample period. In contrast, cocaine - which can only be produced in the Andean region - typically enters Mexico along the Pacific coast via fishing vessels and go-fast boats (U.S. Drug Enforcement Agency, 2011). Thus, the origins for cocaine routes are more flexible, less well-known, and may have changed substantially during the sample period. Moreover, government policies may divert cocaine traffic away from Mexico altogether.[9] For these reasons, the model focuses on domestically produced drugs. In practice, we know little about the quantity of drugs cultivated in each producing municipality, and hence I make the simplifying assumption that each produces a single unit of drugs.

Trafficking paths connect producing municipalities to U.S. points of entry. Formally, a

[8]There are 370 million entries into the U.S. through terrestrial border crossings each year, and 116 million vehicles cross the land borders with Canada and Mexico (U.S. Drug Enforcement Agency, 2011). More than 90,000 merchant and passenger ships dock at U.S. ports each year, and these ships carry more than 9 million shipping containers. Commerce between the U.S. and Mexico exceeds a billion dollars a day.

[9]There is some evidence that shipments of cocaine through Haiti have increased in recent years (U.S. Drug Enforcement Agency, 2011).

trafficking path is an ordered set of nodes such that an edge exists between two successive nodes. Each edge $e \in \mathcal{E}$ has a cost function $c_e(l_e)$, where l_e is the length of the edge in kilometers. The total cost to traverse path p is $w(p) = \sum_{e \in p} c_e(l_e)$, which equals the length of the path. Let $\mathcal{P}_i$ denote the set of all possible paths between producing municipality i and the United States. Each trafficker solves:

$$\min_{p \in \mathcal{P}_i} w(p) \tag{1}$$

This problem, which amounts to choosing the shortest path between each producing municipality and the nearest U.S. point of entry, can be solved using Dijkstra's algorithm (Dijkstra, 1959), which is an application of Bellman's principal of optimality.

4 Direct Effects of Close PAN Victories on Violence

This section uses a regression discontinuity approach to test whether the outcomes of close mayoral elections affect violence in the municipalities experiencing these elections. The qualitative evidence in Section 2 suggests that PAN mayors are more likely than non-PAN mayors to crack down on the drug trade, enlisting the assistance of federal law enforcement. Such crackdowns, in turn, may have contributed to Mexico's pronounced increase in violence in the second half of the 2000s. This section documents that drug trade-related violence increases substantially following the inauguration of PAN mayors. While data on military and federal law enforcement presence are extremely limited, those data that have been accessed suggest a greater military/police presence following close PAN victories, particularly in municipalities where drug trafficking is important. This section also provides quantitative evidence on the mechanisms linking close PAN victories to violence, showing that violence is concentrated where traffickers' control of territory is fragmented. When incumbent traffickers are weakened by a crackdown, this creates an incentive for nearby rivals to violently finish them off and potentially fight amongst themselves for control of the incumbent's territory.

This section first describes the data and identification strategy. It then provides a graphical analysis of the relationship between violence and close election outcomes and examines robustness. Finally, it uses measures of the industrial organization of trafficking to explore mechanisms. To the extent that crackdowns incentivize traffickers to relocate operations, PAN victories could also exert spillovers, which will be examined in Section 5.

4.1 Data

The analysis uses official government data on drug trade-related outcomes, obtained from confidential sources unless otherwise noted. Drug trade related homicides and armed confrontations between authorities and organized criminals occurring between December of 2006 and 2009 were compiled by a committee with representatives from all ministries who are members of the National Council of Public Security (*Consejo Nacional de Seguridad Pública*). This committee meets each week to classify which homicides from the past week are drug trade-related.[10] Drug trade-related homicides are defined as any instance in which a civilian kills another civilian, with at least one of the parties involved in the drug trade. The classification is made using information in the police reports and validated whenever possible using newspapers. The committee also maintains a database of how many people have been killed in armed clashes between police and organized criminals. Confidential daily data on homicides occurring between 1990 and 2008 were obtained from the National Institute of Statistics and Geography (INEGI). Confidential data on high level drug arrests occurring between December of 2006 and 2009 are employed as well. High level traffickers include the kingpins of the major trafficking organizations, the regional lieutenants of these organizations, hired assassins, and the financiers who conduct money laundering operations.

This section also uses official government data on drug trade-related organizations (DTOs), which include major trafficking organizations as well as local gangs. The data list which of Mexico's 2456 municipalities had at least one DTO operating within their limits in early 2008 and also provide the identity of the group if it is a major trafficking organization. They offer the closest possible approximation to pre-period DTO presence available, given that systematic data about DTOs were not collected before this time.

Finally, electoral data for elections occurring during 2007-2008 were obtained from the electoral authorities in each of Mexico's states. The sources for a number of other variables, used to examine whether the RD sample is balanced, are listed in the notes to Table 1.

4.2 Econometric framework

This study uses a regression discontinuity (RD) approach to estimate the impact of PAN victories on violence. The RD strategy exploits the fact that the party affiliation of a given municipality's mayor changes discontinuously at the threshold between a PAN victory and a PAN loss. In general, municipalities where the PAN wins by a large margin are likely to be quite different from municipalities where they lose by a wide margin. However, when we

[10] Previously reported homicides are also considered for reclassification if new information has become available.

narrow our focus to the set of municipalities with close elections, it becomes more plausible that the outcomes are determined by idiosyncratic factors and not by systematic municipal characteristics that could also affect violence. This section examines the plausibility of the RD identifying assumptions in depth, but first it is helpful to specify the regression form.

To perform the RD analysis, I restrict the data to a small window around the PAN win-loss threshold. I choose this bandwidth using the Imbens-Kalyanaraman bandwidth selection rule (2009) and also examine alternative bandwidths. I then estimate a local linear regression using a triangular kernel, which ensures that the weight decays with the distance from the threshold. I estimate the following regression model within the bandwidth:

$$\begin{aligned} y_{ms} = \alpha_0 + \alpha_1 PANwin_{ms} + \alpha_2 PANwin_{ms} \times spread_{ms} \\ + \alpha_3(1 - PANwin_{ms}) \times spread_{ms} + \delta X'_{ms} + \beta X'_{ms} PANwin_{ms} + \alpha_s + \epsilon_{ms} \end{aligned} \quad (2)$$

where y_{ms} is the outcome of interest in municipality m in state s. $PANwin_{ms}$ is an indicator equal to 1 if the PAN candidate won the election, and $spread_{ms}$ is the margin of PAN victory. Some specifications also include α_s, a state-specific intercept and X'_{ms}, demeaned baseline controls. While baseline controls and fixed effects are not necessary for identification, their inclusion improves the precision of the estimates. The sample is restricted to elections in 2007 and 2008 where the PAN won or came in second. I limit the sample to municipalities with at least half a year of violence data prior to the elections, in order to be able to check for violence pre-trends, and show in Appendix Table A5 and Appendix Figure A12 that results are similar when I include the few municipalities that have elections early in 2007 and thus do not have a half year of pre-period data.

Identification requires that all relevant factors besides treatment vary smoothly at the threshold between a PAN victory and a PAN loss. That is, letting y_1 and y_0 denote potential outcomes under a PAN victory and PAN loss, respectively, identification requires that $E[y_1|spread]$ and $E[y_0|spread]$ are continuous at the PAN win-loss threshold. This assumption is needed for municipalities where the PAN barely won to be an appropriate counterfactual for municipalities where the PAN barely lost.

This assumption would be violated if the outcomes of close mayoral elections are determined not by idiosyncratic factors but by a systematic advantage of winners.[11] To assess its plausibility, Table 1 compares 30 municipal crime, political, economic, demographic, road network, and geographic characteristics across the PAN win-loss threshold. The sample is limited to elections with a vote spread of five percentage points or less, a commonly used

[11]For example, Caughey and Sekhon (2011) show that in U.S. House elections between 1942 and 2008, close winners have financial and incumbency advantages.

bandwidth that will be utilized later for the semi-parametric RD analysis. The characteristics are described in Appendix A1, and Appendix Figure A1 shows a map of the close election municipalities, which are located throughout Mexico. Column (1) reports the mean values in municipalities where the PAN barely won, column (2) does the same for municipalities where they barley lost, and column (3) reports the t-statistic on the difference in means.

In no case are there statistically significant differences between municipalities where the PAN lost and municipalities where they won, including for political characteristics such as turnout and the party of the incumbent and for various measures of drug trade-related violence during the pre-period (December of 2006, when these data were first collected, to June of 2007, when the first authorities elected during the sample period were inaugurated).[12] Appendix Table A1 performs the same exercise limiting the sample to municipalities with a vote spread of four, three, and two percentage points or less, documenting similar patterns.

I also estimate the local linear regression specification given in equation (2) using each of the baseline characteristics as the dependent variable and the Imbens-Kalyanaraman optimal RD bandwidth. The coefficients on PAN win are reported in column (4) and t-statistics in column (5). The coefficients tend to be small and statistically identical to zero. RD plots for each outcome are shown in Appendix Figures A2 - A9, and Appendix Table A2 documents that results are similar when I use bandwidths of 5, 4, 3, and 2 percentage points.

While Table 1 shows that a large number of observable characteristics are balanced in municipalities with close elections, one may still be concerned that nearby municipalities are different in ways that systematically influence outcomes in the close election municipalities. For every municipality in the RD sample, I calculate the average of each characteristic in Table 1 in the municipalities that border it. Columns (6) and (7) repeat the local linear regression analysis using these average neighbor characteristics as the dependent variable. Only 1 of the 30 coefficients on PAN win is statistically significant at the ten percent level, providing strong evidence that neighbors' observable characteristics are balanced as well.

Identification also requires the absence of selective sorting around the PAN win-loss threshold. This assumption would be violated, for example, if elections were rigged in favor of the PAN in municipalities that would later experience an increase in violence. To test for sorting around the threshold, I implement McCrary's (2008) test by collapsing the data on close elections to one percentage point vote spread bins and using the observation count in each bin as the dependent variable in equation (2). As shown in Figure 3, this density does not change discontinuously at the threshold. In other words, neither the PAN nor its opponents systematically win close elections. For manipulation of the threshold to be

[12]While there is an economically large difference in surface area, this is driven by a single extremely large municipality, Ensenada.

consistent with Figure 3 and Table 1, there would need to be an equal number of elections rigged in favor of and against the PAN and the 30 characteristics in Table 1 (as well as violence pre-trends, which will be examined subsequently) would need to be the same on average in these municipalities and their neighbors. Unobserved characteristics impacting future violence, in contrast, would need to be different, a scenario that appears unlikely.

The absence of selective sorting is also institutionally plausible. Elections in Mexico are coordinated by a multi-partisan state commission, and genuine recourse exists in the case of suspected fraud. While drug traffickers may have incentives to rig local elections, recall from the discussion in Section 2.2 that prior to the Calderón administration mayors had limited capacity to challenge the drug trade. This study's sample period occurs at the beginning of Calderón's crackdown, when drug traffickers were unlikely to have anticipated how sustained it would be and the role mayors would play. Thus, they may not have found it worthwhile to try to influence local elections. Consistent with this conjecture, killings of mayors by drug traffickers in Mexico began occurring systematically only after the federal crackdown had been sustained for several years, after the conclusion of this study's sample period.

4.3 Graphical Analysis

I begin by providing a graphical analysis of the impact of close PAN mayoral victories on violence. Recall that mayoral races are held every three years at different times in different municipalities. Figure 4 examines average patterns in months following and preceding the election and inauguration of new authorities, Figure 5 shows more detailed monthly patterns, and the online appendix documents additional results and robustness.

More specifically, the six panels in Figure 4 plot violence measures against the PAN margin of victory, with a negative margin indicating a PAN loss. Each point represents the average value of the outcome in vote spread bins of width 0.0025. The solid line plots predicted values from a local linear regression, with separate vote spread trends estimated on either side of the win-loss threshold, and the dashed lines show 95% confidence intervals.

The dependent variable in Panel A is the average probability that a drug trade-related homicide occurs in a given municipality-month during the five months following the inauguration of new authorities. Panel A shows that this probability is around nine percentage points higher after a PAN mayor takes office than after a non-PAN mayor takes office, as compared to a sample average probability of six percent. The mechanisms through which the inauguration of PAN mayors could increase violence will be examined in the next section.

Using the same specification and data source, Panel B shows that violence during the one to five month period between the election and inauguration of new authorities is similar regardless of whether the PAN won or lost.[13] Next, Panel C examines the average monthly probability of drug trade-related homicides during the half year prior to elections. This placebo check documents the absence of a discontinuity at the PAN win-loss threshold prior to the relevant elections, providing further evidence that systematic characteristics related to violence are unlikely to determine close election outcomes.[14] Appendix Figure A10 shows that the patterns in Panels A though C are similar for the drug trade-related homicide rate.

While homicides are classified as drug trade-related by a national committee, it is possible that the information in the police reports used to make this classification systematically differs across municipalities. To explore whether the discontinuity in Panel A reflects the reclassification of homicides by PAN authorities, Panels D through F examine the non-drug trade-related monthly homicide rate per 10,000 municipal inhabitants, for the post-inauguration, lame duck, and pre-election periods, respectively. During the sample period, about half of Mexican homicides were drug-trade related. There are no statistically significant discontinuities, and this is also the case when a dummy measure of non-drug trade-related homicides is used (as documented in Table A3 in the online appendix). As will be discussed subsequently, it is also implausible that PAN authorities discovered enough additional bodies to explain the effects, which reflect a genuine increase in violence.

To shed further light on the relationship between violence and close PAN victories, I estimate equation (2) separately for each month prior to the election and following the inauguration of new authorities. Figure 5 reports the coefficients on PAN win, plotting coefficients for the period lasting from six months prior to the election to six months following the inauguration of new authorities. The dashed lines plot 95% confidence intervals. The lame duck period is excluded due to its varying length by state, which makes it difficult to examine transparently in a month-by-month analysis.

In Panel A, the dependent variable is a dummy equal to one if a drug trade-related homicide occurred in a given municipality-month. The figure documents that prior to the elections, drug trade-related homicides occurred with similar frequency in municipalities where the PAN would later barely lose and barely win. Following the inauguration of new authorities, the PAN win coefficients are large, positive, and statistically significant at the five or ten percent level in all periods except for six months after the inauguration.[15]

As an additional check, I explore the relationship from an alternative perspective that

[13] The length of this lame duck period varies by state.

[14] The probably of drug trade-related violence tends to be higher on either side of the threshold than further away from the threshold because population is also higher; see Appendix Figures A4-d and A5-a.

[15] When the post-period is extended to a year following the inauguration of new authorities, the coefficients are more volatile during the latter half of this period (see Appendix Figure A11). Whether this is due to PAN authorities successfully deterring drug trafficking or results from these authorities being co-opted is not possible to establish definitively.

exploits the full panel variation in the homicide data. Specifically, Panel B plots the γ_τ coefficients from the following differences-in-differences specification against time:

$$y_{mst} = \beta_0 + \sum_{\tau=-T_{ms}}^{T_{ms}} \beta_\tau \zeta_{\tau m} + \sum_{\tau=-T_{ms}}^{T_{ms}} \gamma_\tau \zeta_{\tau m} PANwin_{ms} + f(spread_{ms}) Post_{mst} + \psi_{st} + \delta_m + \epsilon_{mst} \quad (3)$$

where $\{\zeta_\tau\}$ is a set of months-to-election and months-since-inauguration dummies, $Post_{mst}$ is a dummy equal to 1 for all periods t in which the new municipal authorities have assumed power, $f(\cdot)$ is the RD polynomial, which is assumed to take a quadratic form in the graphical analysis, ψ_{st} are state x month fixed effects, and δ_m are municipality fixed effects. ϵ_{mst} is clustered by municipality. The sample is a balanced panel, limited to municipalities with a vote spread of five percentage points or less.

Panel B shows that the magnitudes of the γ_τ coefficients are similar to the month-by-month cross-sectional RD estimates, and Appendix Figure A10 documents that the results are similar for the drug trade-related homicide rate. Finally, Panels C and D repeat the exercise for non-drug trade-related homicides. The cross-sectional RD and panel specifications document the absence of a difference across the PAN win-loss threshold, both before and after the inauguration of new authorities.

4.4 Baseline results and robustness

The graphical analysis shows that drug trade-related violence in a municipality increases substantially after the close election of a PAN mayor, and now I examine the robustness of this relationship. Columns (1) through (3) of Table 2 use equation (2) to estimate the size of the discontinuities in Panels A through C of Figure 4 and Appendix Figure A10.[16] Panel A examines the the average monthly drug trade-related homicide probability and Panel B the drug trade-related homicide rate.[17] The specification includes state fixed effects and controls for the baseline characteristics in Table 1.[18] The post-inauguration period extends to five months following the inauguration of new authorities, after which the monthly analysis suggests that the violence effects become more volatile (Appendix Figure A11), and the

[16] Robust standard errors are reported. When standard errors are clustered by state, the statistically significant effects in Table 2 remain statistically significant.

[17] Analysis of the non drug trade-related homicide rate robustly shows no discontinuity at the PAN win-loss threshold and due to space constraints is presented in Table A3 of the online appendix.

[18] I include either the rate or dummy measures of pre-period violence, and omit the variables for households without water and electricity, since they are highly correlated with marginality, as well as PRI never lost, which is highly correlated with alternations of the mayorship.

pre-election period extends to six months prior to the election.[19]

Column 1 estimates that the average probability that at least one drug trade-related homicide occurs in a municipality in a given month is 8.4 percentage points higher after a PAN mayor takes office than after a non-PAN mayor takes office, and this effect is statistically significant at the one percent level. The drug trade-related homicide rate per 10,000 municipal inhabitants is around 0.05 (s.e. = 0.02) higher following a close PAN victory, which can be compared to the average monthly homicide rate of 0.06. In contrast, the estimated coefficients for the lame duck and pre-inauguration periods are small and statistically insignificant in both panels. Columns (4) and (5) document that the PAN win effect is robust to excluding the state fixed effects as well as both fixed effects and controls[20]

Next, column (6) reports results from the following panel specification, which is analogous to the differences-in-differences specification examined in the graphical analysis:

$$\begin{aligned} y_{mst} = \beta_0 + \beta_E LameDuck_{mst} + \beta_I PostInnaug_{mst} + \gamma_E LameDuck_{mst} PANwin_{ms} \\ + \gamma_I PostInnaug_{mst} PANwin_{ms} + f(spread_{ms}) LameDuck_{mst} \\ + f(spread_{ms}) PostInnaug_{mst} + \psi_{st} + \delta_m + \epsilon_{mst} \end{aligned} \quad (4)$$

$LameDuck_{mst}$ is a dummy equal to one for all periods between the election and inauguration of new authorities, $PostInnaug_{mst}$ is a dummy equal to one for all periods in which the new municipal authorities have assumed power. Pre-election is the omitted category, and ϵ_{mst} is clustered by municipality. The sample is limited to municipalities with a five percentage point vote spread or less, and the sample period is the same as above.

Column (6) specifies $f(spread)$ as linear, estimating that the probability of drug trade-relative violence is 14.7 percentage points higher after a PAN mayor takes office and the monthly drug trade-related homicide rate is 0.09 higher. The coefficients on lame duck × PAN win, consistent with column (2), are substantially smaller and statistically insignificant.

While the RD figures suggest that the data are reasonably approximated by a linear functional form, columns (7), (9), and (11) estimate equation (2) using quadratic, cubic, and quartic vote spread terms, and columns (8), (10), and (12) estimate equation (4) using quadratic, cubic, and quartic forms for $f(spread)$. The estimated effects of close PAN victories are large, positive, and statistically significant across most specifications, with coefficients tending to increase in magnitude when higher order terms are used. Appendix Table A4 documents that results using alternative vote spread bandwidths of 5, 4, or 3 percentage

[19] Results, available upon request, are robust to using periods of alternative length.

[20] The estimated effects for the lame duck and pre-election periods are also similar when state fixed effects and baseline controls are excluded. Moreover, results are robust to excluding just the interaction between PAN win and the controls.

points are similar, regardless of whether equation (2) or equation (4) is used and regardless of the functional form through which vote spread enters.[21]

One concern, examined in Table 3, is that violence following the inauguration of PAN mayors could result from some other correlated political characteristic. The dependent variable in Table 3 is the average monthly probability of drug trade-related homicides during the post-inauguration period, and coefficients are estimated using local linear regression.[22] For comparison, column (1) reports the baseline result from Table 2, column (1).

Next, column (2) distinguishes whether the PAN was the incumbent party. This specification includes the same terms as the baseline and also interacts PAN win, spread, and PAN win $\times$ spread with the incumbency dummy. Recall that Mexican mayors cannot run for re-election, so a new mayor takes office each electoral cycle. The estimated violence effect is large and statistically significant, regardless of whether the PAN held the mayorship previously. Violence increased sharply after the inauguration of PAN mayors and decreased slightly following the inauguration of non-PAN mayors, regardless of the incumbent party.[23]

There are at least two plausible explanations for these patterns. First, recall from Section 2 that mayors typically require assistance from higher levels of government to combat trafficking. Incumbent mayors were elected in 2004 and 2005, before the widespread federal crackdown. Even if they wanted to, it would have been more difficult for these mayors to initiate crackdowns at the beginning of their terms than for mayors elected during the Calderón administration. Many incumbent mayors, unable to crackdown initially, may have already been corrupted by traffickers at the beginning of the sample period. Consistent with this conjecture, Appendix Figure A13 shows that between 2004 and 2006, the outcomes of close elections were uncorrelated with the subsequent homicide rate.

Recall also from Section 2 that mayors often depend on patrons at higher levels of government for their next job. It is possible that PAN incumbent mayors, all elected during the administration of PAN President Vicente Fox (2000-2006), were more likely to have patrons in Fox's faction of the PAN, whereas PAN mayors elected during the Calderón administration were more likely to have patrons in Calderón's faction.[24] Thus, PAN incumbent mayors may have had weak career incentives to aid Calderón's war on drugs.

Mexican state governors control the deployment of state police, disbursement of extensive

[21]When bandwidths of less than 3 percentage points are used, the estimates become extremely noisy.

[22]As documented in Appendix Table A5, results are similar when I instead use a panel data specification.

[23]Prior to the elections, the monthly probability of drug trade-related violence was modestly higher in municipalities with a PAN incumbent (0.067 as compared to 0.048).

[24]The PAN contains a division between traditional, more ideological members and more pragmatic, less ideological members, who tend to have joined the party more recently. Fox, a businessman who joined the PAN in the 1980s, belongs to the latter group, whereas Calderón, who's father was a party founder, belongs to the former (Beer, 2006). Fox supported Calderón's opponent in the primary.

funds, and appointment of various civil service posts. Column (3) shows, however, that the impact of close PAN victories on violence is similar regardless of the party of the governor.[25] Next, column (4) reports a specification that distinguishes whether the PAN candidate faced an opponent from the PRI, which opposed the PAN in around three quarters of elections. There are not statistically significant differences in the PAN win effect.

Columns (5) and (6) examine additional aspects of municipal partisan politics. Column (5) considers close elections where the PRI and PRD - Mexico's other major parties - received the two highest vote shares, replacing the PAN win indicator with a PRI win indicator. While the coefficient on PRI win is positive, it is about half the magnitude of the coefficient on PAN win in the baseline and is not statistically significant. Column (6) includes all close elections (including those in which the PAN was not the winner or runner-up), replacing the PAN win indicator with an indicator equal to one if there was an alternation in political party. The alternation effect is small and statistically insignificant. Overall, these results show that what drives the effects in Table 2 is not a change in party but rather a PAN mayor taking office during the Calderón administration.

I have focused on close elections because they allow for identification of causal effects, whereas it is difficult to interpret the correlations between PAN victories and violence in general because municipalities where the PAN won by a wide margin are quite different from municipalities where they lost by a wide margin. Nevertheless, for the sake of completeness column (7) examines all municipalities with elections in 2007 and 2008 for which the full set of controls are available, reporting results from an ordinary least squares regression of the average monthly drug trade-related homicide probability during the post-inauguration period on the PAN win dummy, controls, and state fixed effects. While the coefficient on PAN win is large and positive, it is noisily estimated.

4.5 Interpretation

This section explores whether crackdowns occur following PAN inaugurations and examines mechanisms linking crackdowns to violence. Data on the allocation of military and federal police cannot be released to individuals outside these institutions, complicating efforts to test for crackdowns directly. Instead, I examine confidential government data on police and military causalities. While these are rare events, occurring in only 12 municipalities with a vote spread of less than 5%, they are the best available measure of crackdowns in 2007-2008.[26]

[25] Only around ten percent of municipalities with close PAN elections in 2007-2008 had a PAN governor during the mayor's subsequent term.

[26] While one could attempt to measure crackdowns using newspapers, much of the press in Mexico does not report on the drug trade due to intimidation. The sample period predates widespread tweeting about the drug war, which has been used to document drug trade-related activity more recently.

Deaths in police-criminal confrontations are ten times higher during the post-inauguration period in municipalities where the PAN barely won as compared to where they barely lost. When I estimate the baseline specification with the average number of post-inauguration confrontation deaths per 10,000 inhabitants as the dependent variable, the PAN win effect of 0.07 (s.e.=0.06) is large, as compared to a sample mean of 0.06 deaths, but noisily estimated. In contrast, the effect in the pre-election period is a precisely estimated zero (-0.01, s.e.= 0.02). When I limit attention to municipalities that had a major drug trafficking organization operating within their limits, the PAN win effect is again large, at 0.19 (s.e.= 0.12), but not quite statistically significant, whereas the PAN win effect is a precisely estimated zero in municipalities without a major drug trafficking organization. Arrests of high level members of the drug trade, while rare, likewise occur more frequently following the inauguration of closely elected PAN authorities.[27]

Recall that 85% of drug trade-related violence consists of drug traffickers killing each other. Based on the evidence on crackdowns summarized above and the qualitative evidence discussed in Section 2, I hypothesize that crackdowns initiated by PAN mayors weaken the incumbent trafficking group, creating incentives for rival trafficking organizations to violently wrest control of the incumbent's territory. While it may not be as lucrative to control a municipality during a crackdown, crackdowns are unlikely to be permanent and thus may not affect the long-run returns to controlling a municipality by much. Incentives to usurp rival territory are plausibly greatest when the territory is nearby, as controlling an entire region allows drug traffickers to monopolize the many organized criminal activities in which they engage. For example, basic economic theory suggests that prices for prostitution will be higher if a trafficking organization controls brothels throughout a region than if a rival controls prostitution in an adjacent municipality. In addition to spurring conflicts between trafficking organizations, crackdowns may result in the removal of a senior trafficker, leading members in his organization to fight over ascension.

To test this hypothesis, I categorize municipalities into four groups using confidential government data on drug trafficking organizations (DTOs). The categories are: 1) municipalities controlled by a major DTO that border territory controlled by a rival DTO (9.5% of the sample), 2) municipalities controlled by a major DTO that do not border territory controlled by a rival DTO (20% of the sample), 3) municipalities controlled by a local drug gang (33% of the sample), and 4) no known drug trade presence (37.5% of the sample).[28]

[27]The federal government does not maintain a database of all drug-related arrests, since most are never prosecuted, so instead I examine confidential government data on high-level drug-related arrests. High level arrests are rare, occurring in only 4 municipalities and 15 municipality months during the sample period. During the post-inauguration period, 49 high level arrests occurred in municipalities where the PAN barely won, as compared to 26 in municipalities where they barely lost.

[28]The major DTOs during the sample period are Beltran, Familia Michoacana, Golfo, Juarez, Sinaloa,

Municipalities with no known drug trade presence had not experienced drug trade-related homicides or illicit drug confiscations at the time the DTO data were compiled, and local authorities had not reported the presence of a drug trade-related group to federal authorities.

For comparison, columns (1) and (2) of Table 4 report the baseline cross-sectional and panel results from columns (1) and (6) of Table 2. Next, column (3) examines the relationship between violence and the territorial structure of trafficking. The dependent variable is the average monthly probability that a drug trade-related homicide occurs during the post-inauguration period, and the specification includes the same terms as the baseline RD as well as interacting PAN win, spread, and PAN win $\times$ spread with dummies for three categories of drug trade presence. No known drug trade presence is the omitted category. Column 4 examines robustness by reporting a panel specification analogous to equation (4), in which dummies for the three categories of drug trade presence are interacted with post-inauguration and post-inauguration $\times$ PAN win. Finally, columns (5) and (6) examine robustness to using a quadratic functional form for the vote spread terms.

Column (3) documents that close PAN victories increase the probability of drug trade-related homicides by a highly significant 53 percentage points in municipalities controlled by a major DTO that border a rival DTO's territory. Amongst municipalities with a major drug trafficking organization that borders a rival, there are an average of 17.4 drug-related homicides during the post-inauguration period when the PAN barely wins, as compared to 1.8 homicides when they lose. It appears highly unlikely that differences of this magnitude are driven by non-PAN authorities failing to discover bodies, many of which are left in public places. The estimated effect of 14.6 percentage points for municipalities controlled by a major DTO that do not border territory controlled by a rival - while smaller - is economically large and statistically significant, suggesting that crackdowns also spur conflicts within criminal organizations. The effects for municipalities with a local drug gang and with no known drug trade presence are small and statistically insignificant, providing further confirmation that the violence data are reasonable. The panel specification in column (4) produces coefficients for municipalities with a trafficking organization that are similar to the estimates from the cross-sectional RD.[29] Finally, columns (5) and (6) show that results are qualitatively similar, albeit somewhat noisier, when a quadratic functional form is used for the vote spread terms.

We would also expect traffickers to fight more over municipalities that are more valuable

Tijuana, and Zetas.

[29] In municipalities with only a local drug gang or with no known drug trafficking presence, a close PAN win is estimated to increase the probability of a drug trade-related homicide by a statistically significant 12.7 and 10.7 percentage points, respectively. While these effects are larger than in column (3), both specifications estimate that the violence effects for these municipalities are smaller than the effects for municipalities with a major DTO.

to control. While it is impossible to measure the size of the illegal economy, I focus on estimating one specific dimension: the cost required for trafficking routes to circumvent a municipality. Estimated detour costs equal the sum of the lengths (in kilometers) of shortest paths from all producing municipalities to the U.S. when paths are not allowed to pass through the municipality under consideration minus the sum of the lengths of all shortest paths when they can pass through any municipality in Mexico. Municipalities with a longer total detour are more costly to circumvent, and thus the traffickers controlling them should be able to charge more for protection and other services to traffickers passing through the municipality.

Columns (7) through (12) interact PAN win or PAN win $\times$ post with standardized total detour costs.[30] A one standard deviation increase in detour costs increases the probability of a drug trade-related homicide following a close PAN victory by around seven percentage points, as compared to an 8.7 percentage point PAN win effect at the sample mean of detour costs. Results are robust to using the panel specification and higher order vote spread terms. I also find that the violent response is lower when a municipality contains a major divided highway (12% of municipalities), which presumably increases the difficulty of extracting rents from traffickers passing through the municipality (results available upon request).

The characteristics examined in Table 4 are highly correlated, and the presence of drug trafficking groups is likely an outcome of the network structure of trafficking. Thus, I cannot separately identify the impacts of territorial ownership and network structure. Nevertheless, together the results suggest that the industrial organization of drug trafficking exerts important effects on the violent response to close PAN victories. I have focused on the above interpretation because qualitative evidence suggests it as particularly plausible, but alternative explanations could also be important. For example, PAN mayors could have received more economic transfers from the PAN federal government, inducing traffickers to fight over who would extort the additional government resources. Over 90 percent of Mexican state and local spending are financed by federal transfers (Haggard and Webb, 2006), but in contrast to law enforcement assistance, resource transfers to municipalities are highly transparent. There are two main funds through which the federal government distributes resources to municipalities: the Fondo para la Infraestructura Social Municipal, which is distributed proportionally to the number of households living in extreme poverty, and the Fondo de Aportaciones para el Fortalecimiento de los Municipios, which is distributed proportionally to municipal population. These characteristics are balanced on the outcomes of close elections, and so transfers are balanced as well.[31]

[30] Results are similar, but more difficult to interpret, when I do not standardize the detour costs measure.

[31] Resource transfers from state to local governments are less transparent, but recall that I don't find

5 A Network Analysis of Spillover Effects

Thus far the analysis has focused on how crackdowns in a given municipality affect that location, but crackdowns may also impact other municipalities by motivating traffickers to relocate their operations. One commonly used approach for identifying such spillovers is to test whether crackdowns increase criminal activity in adjacent areas (see for example Di Tella and Schargrodsky, 2004). While proximity to existing operations may play a role in determining where drug traffickers relocate to, the qualitative evidence in Section 2 emphasizes factors beyond geographic adjacency. Instead of predicting spillovers based on adjacency, this study utilizes the network model of trafficking to identify where spillovers are likely to occur (results using adjacency are also reported). This model incorporates traffickers' cost minimization objective and the constraints imposed by the road network. In this section, I first use data on illicit drug confiscations to test whether the shortest paths network model predicts the diversion of drug traffic following close PAN victories. I then examine whether violence changes in municipalities in which the model predicts a change in drug traffic. Finally, I develop more sophisticated versions of the model that incorporate strategic interactions between traffickers.

5.1 Spillovers and the Shortest Paths Model

In order to test whether crackdowns exert spillover effects, it is necessary to specify a model of where spillovers are likely to occur. Drug trafficking organizations are profit-maximizing entities who face economic constraints, and the shortest paths framework developed in Section 3 models their cost minimization objective and the constraints imposed by the transportation network in a simple and transparent manner. Recall that traffickers take the lowest cost route to the U.S. border, and the cost of traversing each edge is equal to the physical length of the edge unless a close PAN victory has occurred, in which case the edge latency increases to infinity (or, in the robustness checks, by some positive proportion)[32] Because municipal elections happen at different times throughout the sample period, this generates panel variation in predicted routes from producing municipalities to U.S. points of entry.

In the sample of municipalities which have not themselves experienced a close election, which is the focus of the spillovers analysis, variation in predicted trafficking routes results entirely from plausibly exogenous variation in local politics elsewhere in Mexico. If the aim of the exercise were purely predictive, one would potentially allow variation in predicted routes

differences in the PAN win effect by the party of the state governor.

[32] I define close elections as those with a vote spread of five percentage points or less. Results (available upon request) are similar when I instead use municipalities with a vote spread of three percentage points or less or with a vote spread of seven percentage points or less.

to be a function of the outcomes of landslide elections and other time varying characteristics. However, such an approach would not provide a test for spillovers, due to the well-known reflection problem (Manski, 1993). Correlations between municipal politics and drug trade-related outcomes elsewhere could result from environmental factors unrelated to the policies under consideration. For example, support for the PAN and drug trafficking activity could be growing in tandem in a region because of economic factors, generating correlations between municipal politics and violence patterns nearby. Just as when testing for direct effects, it is important when examining spillovers to isolate plausibly exogenous variation. If the outcomes of close elections are as if randomly assigned, then any systematic changes that occur within municipalities when they acquire predicted shortest path routes are likely to be due to spillovers and not to some third factor that caused the PAN to win and violence to simultaneously trend upwards in municipalities where traffic is likely to be diverted.

Like any model, the shortest paths framework is a simplification, and as a result it omits relevant determinants of trafficking. If the model's predictions are too inaccurate, it could fail to detect violence spillovers where they do exist or vice versa. I perform several exercises to shed light on whether the model provides a reasonable picture of where spillovers are most likely to arise. First, I examine the relationship between model predicted routes and actual illicit drug confiscations, the best available proxy for drug traffic, between December of 2006 and 2009. Official government data on municipal-level confiscations of various types of drugs were obtained from confidential sources. To the extent that the model is reasonable, confiscations should increase when a municipality acquires a predicted drug trafficking route if enforcement is held constant. Second, I show that the probability of the patterns I document arising by chance is extremely low. Finally, I extend the model in a variety of ways in the next section.

I examine the relationship between predicted routes and drug confiscations using the following specification:

$$conf_{mst} = \beta_0 + \beta_1 Routes_{mst} + \psi_{st} + \delta_m + \epsilon_{mst} \tag{5}$$

where $conf_{mst}$ is confiscations of domestically produced drugs (marijuana, heroin, and methamphetamine) in municipality m, state s, month t. Both an indicator and a continuous measure of value are explored. $Routes_{mst}$ is a measure of predicted drug trafficking routes, ψ_{st} is a month x state fixed effect, and δ_m is a municipality fixed effect. While the confiscations rate per unit of drug traffic likely differs depending on the political environment, municipal elections occur only once every three years and hence enforcement plausibly stays relatively constant as predicted routes change. The municipality fixed effect ensures that β_1 is identified from within municipality variation, so if enforcement is constant within municipalities over time - an assumption that will be examined subsequently - confiscations will provide a reasonable proxy for actual drug traffic in the context of this specification. Because variation in routes may be correlated across space, the error term is clustered simultaneously by municipality and state-month (Cameron, Gelbach, and Miller, 2011). The sample excludes municipalities with close elections, since the aim of the exercise is to examine spillovers.[33] This empirical approach is summarized in Figure 1.

Panel A of Table 5 reports estimates from equation (5), specifying $Routes_{mst}$ as an indicator equal to one if municipality m contains a predicted route in month t. In column (1), the dependent variable is also an indicator, equal to one if domestically produced drugs (marijuana, heroine, or methamphetamine) were confiscated in the municipality-month. When a municipality acquires a predicted route, the probability of confiscating drugs during a given month increases by around 1.6 percentage points, and this effect is significant at the 1% level. In comparison, the sample mean monthly probability of confiscating drugs is 5.3%. In column (2), the dependent variable equals the log value (in US dollars) of confiscations if confiscations are positive and equals zero otherwise. This measure is always non-negative, as even small confiscations are worth thousands of dollars.[34] Acquiring a predicted trafficking route is associated with an 18.5% increase in the total value of confiscated drugs, and this correlation is significant at the 1% level. In Appendix Table A7, I document similar patterns using the number of predicted routes instead of the indicator for route presence.

These results suggest that the model predicts the diversion of drug traffic following PAN victories, but they could also reflect direct effects of PAN crackdowns. If alternative shortest paths traverse nearby municipalities and if the military and federal police become active in an entire region when deployed to PAN municipalities, there could be a correlation between changes in predicted routes and confiscations that is unrelated to the diversion of drug traffic. In contrast, it is difficult to tell a plausible story in which PAN victories directly affect confiscations along alternative routes located further away. Thus, columns (3) and (4) examine whether the model remains predictive when I exclude municipalities bordering those that have experienced a close PAN victory. The estimated coefficients are similar to those in columns (1) and (2) and are statistically significant at the 5 percent level. Overall, the results in columns (1) through (4) support the hypothesis that PAN mayors crack down on the drug trade, as opposed to simply discovering more bodies than non-PAN authorities. Moreover,

[33] It also excludes producing municipalities, since much of the analysis focuses on the extensive margin of trafficking routes and producing municipalities mechanically contain a predicted trafficking route. Results (available upon request) are robust to including these municipalities.

[34] Working in logs is attractive because drug confiscations are highly right-skewed, with several drug busts confiscating tens of millions of dollars of drugs.

when I force predicted routes to divert around municipalities with close PAN losses, the model loses its predictive power (results available upon request), further supporting the validity of the RD results.

Another concern is that authorities along alternative routes may have increased confiscation efforts in response to a small increase in drug traffic. In this case, the confiscations data would exaggerate the magnitude of the actual increase in drug traffic along alternative routes. I assess this concern by examining whether predicted domestic drug trafficking routes are correlated with cocaine confiscations. While cocaine routes and domestic drug trafficking routes eventually coincide at U.S. entry points, cocaine enters Mexico at locations that are quite distinct from domestic drug production centers. Thus cocaine and domestic drug routes do not coincide in general. If confiscation efforts increase along alternative routes, then cocaine confiscations would plausibly increase as well in municipalities with cocaine traffic. Columns (5) and (6) document that variation in predicted domestic drug routes is uncorrelated with variation in cocaine confiscations.[35]

PAN victories are unlikely to always increase edge costs to infinity, and thus Appendix Figure A14 examines whether the relationship between predicted routes and confiscations is robust to assuming that close PAN victories proportionally increase edge length by a factor α (later I estimate how much PAN victories increase edge costs). The x-axis plots values of α ranging from 0.25 to 10 and the y-axis plots the correspondent coefficient on the routes dummy from equation (5). The cost factors 0.25 and 0.5 serve as placebo checks, since they imply that PAN victories reduce trafficking costs. When routes are predicted using these costs, they are uncorrelated with confiscations. In contrast, the coefficients estimated using cost factors greater than one are similar to the baseline estimate in column (2) of Table 5.

Finally, I randomly assign placebo close PAN victories so as to replicate the number and time pattern of actual close PAN victories. In each month, the number of randomly selected municipalities that are infinitely costly to traverse increases by the number of close PAN victories that actually occurred that month. I calculate predicted routes and regress confiscations on an indicator for the presence of a predicted route (along with municipality and state x month fixed effects), repeating this exercise 1000 times and plotting the coefficients in Appendix Figure A15. These regressions are analogous to the regression reported in column (2) of Table 5. Only six of the coefficients are statistically different from zero at the 5% level, and the coefficient from column (2) is more than three standard deviations above the mean, implying that the patterns in Table 5 are unlikely to have arisen by chance.

[35]Results are similar when I limit the sample to municipalities with cocaine confiscations during the beginning of the sample period. Because of the municipality fixed effects, municipalities without cocaine confiscations only affect the routes coefficient through their influence on the state x year fixed effects.

These results show that the shortest paths model predicts the diversion of drug traffic following PAN victories. I now test whether violence changes when predicted routes change, estimating the same panel specification as above with violence as the dependent variable. The results provide strong evidence that crackdowns increase violence along alternative drug routes. First, column (1) of Table 6 shows that the presence of a predicted route increases the monthly probability of drug trade-related homicide by 1.3 percentage points (s.e.=0.005), as compared to the sample average probability of 4.4%. Column (2) distinguishes whether the municipality contains only one or more than one route. One might expect violence to concentrate where multiple routes coincide, but the coefficients on the one and more than one route indicators are statistically identical. Columns (3) and (4) use the drug trade-related homicide rate as the dependent variable, documenting similar patterns. Next, columns (5) and (6) examine the limited sample that excludes municipalities bordering a close PAN victory. While the effects decline somewhat in magnitude and are not statistically significant, I cannot reject that the routes coefficients in the full and limited samples are statistically identical. Finally, column (7) documents that predicted routes are uncorrelated with the non-drug homicide rate, alleviating concerns that municipalities on alternative routes experience growing violence for reasons unrelated to the drug trade.

I also show that a conventional reduced form approach is unable to locate spillovers unless it is combined with economically informed predictions about where spillovers are likely to occur. I replicate the RD specification from Section 4, except that the dependent variable is violence in municipalities bordering a close election municipality instead of violence in the municipality experiencing the close election. Appendix Table A8, column (1) shows that when I include all neighboring municipalities, the coefficient on PAN win is statistically indistinguishable from zero. To shed light on why this specification does not find spillovers, I divide municipalities into three groups: 1) those that border a close election municipality on a shortest path trafficking route and that are on the shortest path detour around that municipality, 2) those that border a close election municipality on a shortest path route but are not on the detour around the close election municipality, and 3) those that border a close election municipality that is not located on a shortest path trafficking route. Columns (2) through (4) document a large, statistically significant increase in violence for the first group of municipalities, whereas the PAN win coefficient is small and statistically insignificant for the latter two groups. This shows that violence increases following PAN victories only in those neighboring municipalities where drug traffic is likely to be diverted.

5.2 A richer trafficking model

The shortest paths model assumes that there are no interactions between traffickers, but in reality traffickers may care about other traffickers' routing choices. As drug traffic on an edge increases, the probability of violent conflict with other traffickers may change, the quality of hiding places may decline (particularly at U.S. points of entry), and law enforcement may direct more or less attention per unit of traffic. This section extends the trafficking model to allow the cost of traversing an edge to change as a function of the amount of drug traffic on that edge. The shortest paths model is a special case of this more general model where congestion costs are assumed to be zero. I also discusses additional extensions, such as allowing traffickers to face different edge costs depending on their DTO affiliation. Due to space constraints, most relevant technical details are discussed in the online appendix.

As in the shortest paths model, every origin produces a unit of drugs and has a trafficker who decides how to transport the municipality's supply of drugs to U.S. points of entry, whose size is given by the number of commercial lanes for terrestrial border crossings and the container capacity for ports. All U.S. entry points pay the same international price for a unit of drugs. Each edge e has a cost function $c_e(l_e, x_e)$, where l_e is the length of the edge and x_e is the total drug flow on edge e. A trafficker's objective is to minimize costs of transporting his municipality's drugs, taking aggregate flows as given. Recall from Section 2 that most trafficking decisions are made within local cells, so the assumption that traffickers are small appears reasonable and simplifies the analysis considerably. Later, I show that results are robust to modelling traffickers as non-atomic decisionmakers.

In equilibrium, the costs of all routes used to transport drugs from a producing municipality to the U.S. are equal and less than the cost that would be experienced by reallocating traffic to an unused route. These conditions were first formalized by John Wardrop (1952) and characterize the Nash equilibrium of the game. Formally, an equilibrium satisfies:

1. For all $p,\ p' \in \mathcal{P}_i$ with $x_p,\ x_{p'} > 0$, $\sum_{e \in p'} c_e(x_e, l_e) = \sum_{e \in p} c_e(x_e, l_e)$.

2. For all $p,\ p' \in \mathcal{P}_i$ with $x_p > 0\ x_{p'} = 0$, $\sum_{e \in p'} c_e(x_e, l_e) \geq \sum_{e \in p} c_e(x_e, l_e)$.

where $\mathcal{P}_i$ denotes the set of all possible paths between producing municipality i and U.S. entry points and x_p denotes the flow on path p. An equilibrium routing pattern always exists, and if each c_e is strictly increasing, the equilibrium is unique. The equilibrium routing pattern is not typically socially optimal since traffickers do not internalize the congestion externalities.

Beckmann, McGuire, and Winsten (1956) proved that the equilibrium can be characterized by a straightforward optimization problem, which is given in the estimation appendix. For a given network, set of supplies, and specification of the congestion costs $c_e(\cdot)$, the problem can be solved using numerical methods, also detailed in the appendix.

In contrast to the shortest paths model, edge costs in the more general model are not directly observed. To make progress, I assume that congestion costs take a Cobb-Douglas form. In the most parsimonious specification, edges connecting Mexico to the U.S. (which by definition are of length zero) impose costs equal to $\phi_t(flow_e/lanes)^\delta$ for terrestrial border crossings and $\phi_p(flow_e/containers)^\delta$ for ports, where $\{\phi_t, \phi_p, \delta\}$ are parameters that will be estimated, *lanes* is the number of commercial crossing lanes, and *containers* is the port container capacity. δ captures the shape of congestion costs, and $\{\phi_t, \phi_p\}$ scale these costs to the same units as physical distance. Interior edges are not congested: $c_e^{int}(l_e, x_e) = l_e$. This model resembles the shortest paths model, except that traffickers incur costs to enter the U.S. that depend on the amount of drug traffic using the entry point, normalized by the entry point's size. In the appendix I also estimate a more flexible specification with six ϕ parameters for different sizes of terrestrial crossings and ports. Finally, I estimate a specification with congestion costs on crossing and interior edges: $C_e^{int} = l_e(1 + \phi_{int} flow_e^\gamma)$, where ϕ_{int} and γ are parameters whose interpretation is analogous to ϕ_t/ϕ_p and δ.[36]

The above parameters, as well as a scaling parameter κ that maps model-predicted flows to model-predicted confiscations, are estimated using the simulated method of moments (SMM).[37] Every choice of the model's parameters generates a set of moments that summarize model-predicted confiscations, and I estimate the parameters by matching these moments to their counterparts calculated from cross-sectional data on the value of illicit drugs confiscated during the beginning of the sample period.[38] The appendix lists the moments (Table A9), specifies the SMM objective, and discusses inference.

As is often the case with choice problems, the SMM objective is not globally convex. Standard gradient methods are likely to perform poorly, and thus I minimize the objective using simulated annealing (Scott Kirkpatrick, C. Daniel Gelatt, and Mario Vecchi, 1983). Details about the estimation are provided in the online appendix. It is not possible to guarantee that an estimation procedure will find the global minimum of a non-convex objective, but Monte Carlo type simulations suggest that the trafficking problem is well-behaved.

Appendix Table A10 reports the parameter estimates for the three specifications outlined above, and model predicted pre-period routes are shown in Figure 2.[39] All three specifications estimate convex congestion costs on U.S. points of entry ($\delta > 1$), and interior congestion appears modest, with congestion costs at U.S. points of entry about 39 times larger than

[36] Results are robust to specifying interior costs as $l_e + \phi_{int} flow_e^\gamma$.

[37] κ likely varies with the local environment, but it is not possible to estimate this dependence.

[38] This lasts from December 2006 (when the data become available) until the first authorities elected during the sample period took office in July 2007.

[39] Conley standard errors are in brackets, and robust standard errors are in parentheses. Figure 1 uses the parameter estimates from column (1). Routes using the parameters from columns (2) or (3) are similar.

total interior congestion costs. This appears plausible, as U.S. entry points are bottlenecks with a large law enforcement presence. All specifications estimate that total congestion costs are nearly as large as total distance costs. The appendix shows that - as expected given the SMM approach - the model is predictive of pre-period confiscations.

The more challenging - and relevant - test is whether the model fitted on pre-period confiscations can predict changes in confiscations during later periods. Panel B of Table 5 uses equation (5) (the same specification used to test the shortest paths model) to compare within-municipality variation in predicted routes and confiscations. The routes are calculated using the three congestion parameters in column (1) of Table A10.[40]

While congestion changes the predicted routes somewhat, the congestion model offers only a modest improvement in predictive power.[41] Columns (1) and (2) of Table 5 estimate that when a municipality acquires a predicted route, the probability of confiscations increases by 1.5 percentage points, and the value of confiscations increases by around 19.5%. Both coefficients are similar to the shortest paths estimates in Panel A. Columns (3) and (4) document robustness to excluding municipalities bordering a municipality that has experienced a close PAN victory, and columns (5) and (6) show that correlations between predicted domestic routes and the presence/value of cocaine confiscations are low. These results are consistent with a world in which the risk of drug confiscations, by authorities and other criminals, increases with time on the road, and hence traffickers prefer to use direct routes.

The violence spillovers are also similar to those estimated using shortest path routes. Panel B of Table 6 shows that the probability of drug trade-related violence increases substantially when a municipality acquires a predicted trafficking route. Column (2) suggests that this violence is concentrated in municipalities where multiple trafficking routes coincide, but this result should be interpreted cautiously since the shortest paths model estimates similar violence effects regardless of the number of routes.

Thus far, the model has not imposed costs for transporting drugs through territory controlled by a rival DTO. With ideal data, one could estimate these costs by matching predicted routes for each DTO to confiscations made from that DTO, but data are not available on which DTOs the confiscations were made from. Additionally, 51% of producing municipalities were controlled by local gangs, and there is not information on which larger organizations, if any, these groups coordinated with to transport drugs. Finally, introducing territorial costs would imply that the edge latencies are player-specific, which complicates the game considerably. A trafficking equilibrium may not exist, even when restrictive functional

[40]Variation in these routes is most highly correlated with variation in actual confiscations. Appendix Tables A11 and A12 document robustness to using the parameters in columns (2) and (3) of Table A10.

[41]The partial correlation coefficient between the routes dummy calculated using the model with congestion and the value of confiscations is 0.018, as compared to 0.014 for the shortest paths model.

forms are assumed for the latencies (Gairing, Monien, and Tiemann, 2011).

Because least cost routes between producing municipalities controlled by a major DTO and U.S. points of entry tend to pass primarily through territory controlled by that DTO, territorial costs may not influence the trafficking equilibrium much even if passing through another DTO's territory is costly. While incorporating accurate estimates of these costs would plausibly improve the model's predictive power, it is less clear that estimates from available data would introduce more realism than noise. In the online appendix, I estimate a model in which non-atomic decisionmakers, consisting of a single representative for each DTO and drug producing gang, minimize the costs of transporting their group's drugs to the U.S. Costs are incurred from passing through a rival's territory, as well as from distance or distance and congestion.[42] The moments used to estimate the territorial cost parameters are listed in Appendix Table A9. To solve the trafficking game for a given set of parameters, I iterate the best response functions to convergence.[43] Appendix Table A13 shows that the coefficients from regressing actual confiscations or drug-related homicides on the territorial predicted routes dummy are positive and statistically significant, regardless of whether congestion costs are included. I also regress actual confiscations on both the routes dummy from this model and the routes dummy from the model without territorial costs. Consistent with the conjecture that territorial costs are difficult to infer from available data, only the latter coefficient is large and statistically significant.

If the effects of PAN victories on trafficking are similar regardless of the margin of victory, the model's predictions could also plausibly be improved by imposing a cost to pass through all municipalities with a PAN mayor. In the online appendix, I estimate how much close PAN victories increase trafficking costs and then predict routes by plugging in this cost for all PAN municipalities, regardless of the margin of victory. As in the baseline, I estimate parameters using close elections in order to address the reflection problem. Table A9 lists the moment conditions. Whereas the baseline model matches only levels of predicted and actual confiscations, the parameters in this richer model are identified in part from matching changes in actual and predicted confiscations. While in theory one could estimate the parameters using confiscation patterns from the end-of-period cross-section, in practice this leads to extremely imprecise parameter estimates. Significant information is gained by examining how routes change over time as municipal politics change.

To predict routes for each period, I use a version of the trafficking model where edge latencies increase by the amount estimated through SMM when a PAN mayor elected during

[42] Local gangs pay a cost to pass through a major DTO's territory.

[43] Although an equilibrium is not guaranteed to exist, simulations show that the best responses always converge to a unique equilibrium regardless of the starting point.

the Calderón administration takes office, regardless of the margin of victory. This model cannot be validated using confiscations data because confiscations from all periods are used to estimate the parameters, and this is why the baseline model did not estimate political costs. Table A13 shows that when I estimate this model without congestion, the coefficient from regressing drug trade-related homicides on the routes dummy is positive, highly significant, and similar to the estimate from the baseline shortest paths model.[44] In contrast, the routes coefficient in the version with congestion is not statistically significant, and the congestion parameters are noisily estimated. This suggests that there is not enough variation in the data to precisely estimate both political and congestion costs simultaneously.

As a final extension, the online appendix also repeats the above exercise using labor market outcomes from the National Occupation and Employment Survey as the dependent variable. Table A14 shows that there is not an economically or statistically significant correlation between the predicted routes dummy and male labor force participation, regardless of whether routes are predicted using the shortest paths or congestion models. In contrast, the presence of a predicted trafficking route lowers female labor force participation by 1.26 percentage points (s.e.= 0.57), relative to an average female participation rate of 51 percent. Table A14 also shows that predicted routes are uncorrelated with the wages of formal sector workers, whereas informal sector wages - measured as monthly profits divided by hours worked - fall by around 2.3 percent (s.e.= 1.3) when a municipality acquires a predicted route.[45] The analysis of wages is limited to prime age males to reduce concerns about selection bias. Further details are given in the appendix.

These results suggest that women are less likely to work outside the home when violent drug traffickers come to town. Cultural norms may make it less desirable for women to participate in the labor force when violence occurs nearby, particularly given the public and graphic nature of drug violence in Mexico, or women might be more vulnerable to extortion by traffickers, given that they are concentrated in the informal sector.[46] Recall from Section 2 that such extraction is widespread. If informal sector workers report their earnings as net of the rents extracted by traffickers, then extortion could explain the decline in reported wages.[47] Investigation of the channels through which drug trafficking impacts labor markets is an important area for future research.

[44] Results are also similar when the costs of passing through any municipality with a PAN mayor elected during the Calderón administration are assumed to be infinite.

[45] Formal sector workers are those that contribute to the federal social security system.

[46] The presence of drug trafficking could also draw people into illicit employment that would not be reported in labor survey data, although this would likely affect men at least as much as women.

[47] In contrast, formal sector workers are likely to earn a fixed hourly wage or salary, and presumably report this in the labor market survey.

6 Policy Applications

This study has shown that Mexican drug trafficking policy substantially increased violence. Potential policy interpretations of the results vary widely, as expected given the complex and controversial nature of the war on drugs, and there are clearly no easy solutions to the problems that Mexico faces. This section discusses several policy interpretations, which alternatively advocate drug legalization, de facto decriminalization, a continuation of the status quo, and the use of quantitative tools to inform law enforcement allocations. The section also extends the network model so that it can be used for policy analysis.

One potential conclusion is that the monetary and human costs of combating trafficking exceed the benefits, and thus Mexico should legalize drugs. While the government's aim was to raise traffickers' costs enough that they would rarely find it profitable to operate in Mexico, drugs are still being trafficked in large quantities, albeit this study suggests along somewhat different routes. Drug consumption in the hemisphere has not declined, whereas the U.S. cocaine price has fallen (U.N. World Drug Report, 2011). Moreover, if drugs were legalized, traffickers might have fewer incentives to corrupt Mexican institutions. While legalization would save monetary resources and plausibly lives, it does not appear particularly likely in the near future. Hemispheric politics create strong incentives to combat trafficking, and even the most pro-legalization Latin American countries advocate legalizing only marijuana, as hard drugs pose varied health risks. Moreover, Mexicans tend to have little sympathy for traffickers, given their varied extortionary activities (Díaz-Cayeros et al., 2011).

Some have instead suggested that the government should broker a deal with DTOs exchanging a *de facto* decriminalization of trafficking for the cessation of predatory activities and/or violence (Kleiman, 2011). While predation impacts Mexicans more than drug transport, it is not clear that such a deal could be sustained, given the large number of DTOs, the limited control that DTO leaders have over their ranks, and international pressures.

An alternative view, advocated by policymakers such as Calderón, emphasizes that continued crackdowns are imperative because DTOs use their large profits to control the police department, the press, and other fundamental institutions. Crackdowns may increase violence in the medium term, but in the long run weakened traffickers will have fewer resources to co-opt the state. It is deeply problematic when DTO assassins are the police homicide unit and DTO kidnappers staff the police anti-kidnapping division, as has often been true in Mexico historically (Molloy and Bowden, 2011). However, it is unclear whether crackdowns reduce traffickers' profits enough to constrain their corrupting influence and whether drug interdiction is a necessary component in strengthening institutions.

Mexican interdiction policy has frequently been criticized for indiscriminately targeting traffickers rather than focusing resources through a more systematic and theoretically informed approach (Guerrero, 2011; Kleiman, 2011). Thus, there is plausibly scope to improve interdiction by using a systematic framework to model traffickers' responses to different patterns of law enforcement deployment. Improving law enforcement efficiency seems desirable, but this study underlines that collateral consequences may also result. First, a well-coordinated disruption of trafficking routes may increase violence, at least in the short run. It may also cause international spillovers, with more cocaine trafficked through the Caribbean and more Americans growing marijuana and cooking meth in their closets. While traffickers' would have lower profits, this may not be welfare improving for the Americas as a whole. Finally, if trafficking and other criminal activities are substitutes, unemployed traffickers may expand their extortion, kidnapping, and theft operations.

Quantitatively assessing which of the above perspectives is welfare maximizing would require a large number of assumptions, in part because neither legalization nor the long-run effects of Mexico's drug war have been observed and in part because it is controversial what Mexico's drug policy objectives should be. More research is needed on whether crackdowns strengthen institutions, on the likely costs and benefits of legalization, and on the elasticity of substitution between trafficking and other criminal activities. Because interdiction is likely to continue in the near future, I focus here on how the trafficking model could inform interdiction and on how adverse consequences could be reduced.

Section 5 aimed to isolate causal effects and thus used exogenous policy variation. In order to apply the trafficking framework to policy analysis, it is necessary to endogenize government decisionmaking. I do this by embedding the trafficking model in a Stackelberg network game (Baş and Srikant, 2002; Stackelberg, 1952). In the first stage, the government (a single player) decides how to allocate law enforcement resources to edges in the road network, subject to a budget constraint. Traffickers' cost of traversing an edge increases when law enforcement resources are placed on it. In the second stage traffickers simultaneously select the least cost routes to transport their drugs to the U.S. The government's objective is to maximize the total costs that traffickers incur, and each trafficker minimizes his own costs. This framework can accommodate multiple types of resources with deployment costs that vary by edge.

There are several things to note about how the network structure conditions the equilibrium allocation of law enforcement resources. First, while a naive policy might allocate law enforcement to edges with the most drug traffic, the network model highlights that the extent to which law enforcement affects trafficking costs depends on available detours. In fact, increasing an edge cost can decrease total trafficking costs if there are externalities from congestion. This result, known as Braess's paradox, occurs for around fifteen percent of the edges in the congested trafficking equilibrium.[48] Moreover, the effects of law enforcement in different locations are interconnected through the network structure, implying that resource allocation decisions should be made jointly rather than on a location-by-location basis.

The online appendix provides an illustrative example of how this framework can be used to inform the allocation of scarce law enforcement resources. I show that the government's law enforcement allocation problem is NP hard, which implies that the time required to solve for the optimum increases quickly as the size of the problem grows. Intuitively, the problem is challenging because allocating resources to two edges at the same time might increase the objective function more than the summation of changes in the objective when resources are allocated to each edge separately. Hence the order in which a solution algorithm proceeds may matter. I develop an algorithm for solving the game and examine robustness to changing the algorithm's details. I also discuss how the model could be extended to provide a more detailed framework for analyzing Mexican military and police deployment.

This exercise illustrates how the network model can contribute unique information to interdiction efforts. For example, if the government has enough resources to triple the latencies on 25 of the network's 18,000 edges, the model predicts that it can increase the total costs incurred by traffickers by 17%. Appendix Figure A16 shows that the 25 edges chosen using the network model differ from the edges that would be selected if Mexico deployed resources to the 25 most trafficked edges or to the 25 most violent municipalities.

A major concern with improving interdiction is that violence may increase as a result. This could be explicitly incorporated into the model by including a violence term in the government's resource allocation cost function. The magnitude of the edge-specific violence cost would depend on regional patterns of DTO territorial control, the edge's centrality to the trafficking network, and potentially other relevant characteristics.

Moreover, if the government could succeed at lowering police corruption and strengthening criminal justice institutions, efforts to improve the allocation of law enforcement could plausibly reduce trafficking while generating fewer negative externalities for Mexican society. For example, if the state could credibly commit to long-term increases in non-corrupt law enforcement in certain locations, the present discounted value of controlling illicit activities in these locations would fall and there would be a lower return to violently usurping them. Examining how criminal justice reforms can be most effectively implemented is a central question for future research, regardless of the drug policies that Mexico pursues.

[48] For examples of Braess's paradox in traffic congestion in Seoul, New York, Berlin, Boston, London, and elsewhere, see Bombardini and Trebbi (2012); Youn, Gastner, and Jeong (2008); Easley and Kleinberg (2008, p. 71); and Knodel (1969, p. 57-59). Just as the players in the prisoners dilemma could be made better off by removing the defect option, traffickers can be made better off by removing an edge that was previously used in equilibrium.

7 Conclusion

This study examines the direct and spillover effects of Mexican policy towards the drug trade, developing three sets of results. First, regression discontinuity estimates show that drug trade-related violence in a municipality increases substantially after the close election of a PAN mayor. The empirical evidence suggests that the violence largely reflects rival traffickers' attempts to wrest control of territories after crackdowns initiated by PAN mayors have challenged the incumbent criminals. Second, an economic model of equilibrium trafficking routes predicts the diversion of drug traffic following close PAN victories. When drug traffic is diverted to other municipalities, violence in these municipalities increases. Finally, I show that the network approach can serve as a tool for the allocation of law enforcement.

These results demonstrate how traffickers' economic objectives and constraints imposed by the routes network affect the policy outcomes of the Mexican Drug War. While there are unlikely to be any easy solutions to the challenges posed by the drug trade, the results suggest that developing a more detailed understanding of how governments and organized criminals interact in networks could improve the allocation of scarce public resources, in Mexico and a number of other contexts. This study has focused on the shorter-term consequences of the Mexican Drug War because at the time of writing, any longer term impacts on institutional quality and security had yet to be realized. Examining the conditions under which crackdowns on organized crime lead to long-term changes in these outcomes is a particularly central question for future research.

References

Acemoglu, D. and M. Dell (2009): "Beyond Neoclassical Growth: Technology, Human Capital, Institutions and Within-Country Differences," *American Economic Journal: Macroeconomics*, 2, 169–188.

Angrist, J. and A. Kugler (2008): "Rural windfall or a new resource curse? Coca, income, and civil conflict in Colombia," *The Review of Economics and Statistics*, 90, 191–215.

Ball, M., B. Golden, and R. Vohra (1989): "Finding the most vital arcs in a network," *Operations Research Letters*, 8, 73–76.

Başar, T. and R. Srikant (2002): "A Stackelberg network game with a large number of followers," *Journal of optimization theory and applications*, 115, 479–490.

Beckmann, M., C. McGuire, and C. Winston (1956): *Studies in the Economics of Transportation*, Yale University Press.

Bhojraj, S., P. Hribar, M. Picconi, and J. McInnis (2009): "Making sense of cents: An examination of firms that marginally miss or beat analyst forecasts," *The Journal of Finance*, 64, 2361–2388.

Bollen, N. and V. Pool (2009): "Do hedge fund managers misreport returns? Evidence from the pooled distribution," *The Journal of Finance*, 64, 2257–2288.

Braess, D. (1968): "Über ein Paradoxon aus der Verkehrsplanung," *Mathematical Methods of Operations Research*, 12, 258–268.

Brown, G., M. Carlyle, J. Salmeron, and K. Wood (2005): "Analyzing the vulnerability of critical infrastructure to attack and planning defenses," *INFORMS tutorials in operations research*, 102–123.

Cameron, A., J. Gelbach, and D. Miller (2006): "Robust inference with multi-way clustering," *National Bureau of Economic Research Cambridge, Mass.*

Conley, T. (1999): "GMM estimation with cross sectional dependence," *Journal of Econometrics*, 92, 1–45.

Di Tella, R. and E. Schargrodsky (2004): "Do police reduce crime? Estimates using the allocation of police forces after a terrorist attack," *The American Economic Review*, 94, 115–133.

Díaz-Cayeros, A., B. Magaloni, A. Matanock, and V. Romero (2011): "Living in Fear: Mapping the Social Embeddedness of Drug Gangs and Violence in Mexico," *Unpublished Manuscript.*

Dijkstra, E. (1959): "A note on two problems in connection with graphs," *Numerische mathematik*, 1, 269–271.

Duggan, M. and S. Levitt (2002): "Winning Isn't Everything: Corruption in Sumo Wrestling," *American Economic Review*, 92, 1594–1605.

Easley, D. and J. Kleinberg (2010): *Networks, crowds, and markets: Reasoning about a highly connected world*, Cambridge University Press.

Frank, M. and P. Wolfe (1956): "An algorithm for quadratic programming," *Naval Research Logistics Quarterly*, 3, 95–110.

Gambetta, D. (1993): *The Sicilian Mafia*, Harvard University Press.

Guerrero-Gutiérrez, E. (2011): "Security, Drugs, and Violence in Mexico: A Survey," *7th North American Forum, Washington D.C.*

Imbens, G. and K. Kalyanaramang (2009): "Optimal bandwidth choice for the regression discontinuity estimator," *National Bureau of Economic Research Cambridge, Mass.*

Imbens, G. and T. Lemieux (2008): "Regression discontinuity designs: A guide to practice," *Journal of Econometrics*, 142, 615–635.

Isacson, A. (2010): "Colombia: Don't Call it a Model," *Policy Document: Washington Office on Latin America.*

Israeli, E. and R. Wood (2002): "Shortest-path network interdiction," *Networks*, 40, 97–111.

Kirkpatrick, S., C. Gelatt, and M. Vecchi (1983): "Optimization by simulated annealing," *Science*, 220, 671–680.

Kleiman, M. (2011): "Surgical Strikes in the Drug Wars," *Foreign Affairs.*

Knodel, W. (1969): *Graphentheoretische Methoden und ihre Anwendungen*, Springer-Verlag.

Krueger, A. and A. Mas (2004): "Strikes, Scabs, and Tread Separations: Labor Strife and the Production of Defective Bridgestone/firestone Tires." *Journal of Political Economy*, 112, 253–289.

Lee, D., E. Moretti, and M. Butler (2004): "Do voters affect or elect policies? Evidence from the US House," *The Quarterly Journal of Economics*, 119, 807–859.

Leech, G. (2000): "The Failure of Coca Eradication in Peru and Bolivia," *Colombia Journal.*

Levitt, S. and S. Venkatesh (2000): "An Economic Analysis of a Drug-Selling Gang's Finances," *The Quarterly Journal of Economics*, 115, 755–789.

Lim, C. and J. Smith (2007): "Algorithms for discrete and continuous multicommodity flow network interdiction problems," *IIE Transactions*, 39, 15–26.

Lin, M., N. Qian, and J. Liu (2008): "More women missing, fewer girls dying: The impact of abortion on sex ratios at birth and excess female mortality in Taiwan," *National Bureau of Economic Research Cambridge, Mass.*

Malik, K., A. Mittal, and S. Gupta (1989): "The k most vital arcs in the shortest path problem," *Operations Research Letters*, 8, 223–227.

Manski, C. (1993): "Identification of endogenous social effects: The reflection problem," *The Review of Economic Studies*, 60, 531–542.

McFadden, D. (1989): "A method of simulated moments for estimation of discrete response models without numerical integration," *Econometrica*, 995–1026.

Pakes, A. and D. Pollard (1989): "Simulation and the asymptotics of optimization estimators," *Econometrica*, 1027–1057.

Rios, V. (2011a): "Understanding Mexico's Drug War," *Manuscript: Harvard University Department of Government.*

——— (2011b): "Why did Mexico become so violent? Criminal diversification and drug-related violence: The case of La Familia," *Manuscript: Harvard University Department of Government.*

Secretaría de Salud, CONADIC (2008): *National Addictions Survey.*

Secretaría de Seguridad Pública (2010): *Informe del Estado de la Seguridad Pública en México.*

Secretariado Ejecutivo del Sistema Nacional de Seguridad Pública (2008): *National criminal incidence.*

Shannon, E. (1988): *Desperados: Latin drug lords, US lawmen, and the war America can't win*, Viking.

Shirk, D. (2011): "Drug Violence and State Responses in Mexico," *Manuscript: University of San Diego.*

Stackelberg, H. (1952): *The theory of the market economy*, William Hodge.

Stock, J., J. Wright, and M. Yogo (2002): "A survey of weak instruments and weak identification in generalized method of moments," *Journal of Business and Economic Statistics*, 20, 518–529.

United Nations International Drug Control Programme and United Nations Office on Drugs and United Nations Office for Drug Control and Crime Prevention (2011): *World Drug Report*, United Nations Publications.

United States Drug Enforcement Agency (2011): *Drug Trafficking in the United States.*

Varese, F. (2005): *The Russian Mafia: private protection in a new market economy*, Oxford University Press.

Wardrop, J. (1952): "Some Theoretical Aspects of Road Traffic Research," *Proceedings of the Institution of Civil Engineers*, 1, 325–378.

Wolfers, J. (2006): "Point shaving: Corruption in NCAA basketball," *The American Economic Review*, 96, 279–283.

Youn, H., M. Gastner, and H. Jeong (2008): "Price of anarchy in transportation networks: Efficiency and optimality control," *Physical review letters*, 101, 128701.

Zitzewitz, E. (2011): "Forensic Economics," *Forthcoming Journal of Economic Literature.*

Table 1: Pre-characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Own municipality					Neighboring muns.	
	5% vote spread PAN won	PAN lost	t-stat on means difference	RD estimate	t-stat on RD estimate	RD estimate	t-stat on RD estimate
Crime characteristics							
Drug-trade related homicides	0.18	0.11	(0.41)	0.09	(0.43)	0.14	(0.80)
Drug-trade related homicide dummy	0.03	0.04	(-0.51)	-0.01	(-0.38)	-0.02	(-0.47)
Police-criminal confrontation deaths	0.09	0.15	(-0.57)	-0.08	(-0.43)	0.04	(0.41)
Confrontation deaths dummy	0.04	0.04	(0.01)	0.01	(0.12)	0.01	(0.25)
Annual homicide rate (1990-2006)	1.37	1.5	(-0.46)	-0.07	(-0.20)	-0.07	(-0.31)
Mun. taxes per capita (2005)	59.84	56.75	(0.23)	15.86	(0.84)	9.01	(0.42)
Turnout	0.61	0.59	(0.99)	0.02	(0.85)	0	(0.71)
PAN incumbent	0.27	0.32	(-0.61)	0	(0.01)	-0.07	(-1.03)
PRD incumbent	0.17	0.13	(0.63)	0.02	(0.30)	0	(-0.02)
% alternations (1976-2006)	0.31	0.31	(-0.20)	0.01	(0.27)	-0.04	(-1.85)*
PRI never lost (1976-2006)	0.07	0.07	(-0.04)	-0.01	(-0.13)	0.01	(0.36)
Population (2005)	60259	50991.28	(0.35)	23169.85	(0.64)	3.67	(0.81)
Population density (2005)	220.23	191.05	(0.42)	8.63	(0.08)	-37.53	(-0.33)
Migrants per capita (2005)	0.02	0.02	(-0.69)	0	(-0.45)	0	(0.08)
Income per capita (2005)	4.29	4.48	(-0.53)	-0.14	(-0.29)	-0.05	(-0.11)
Malnutrition (2005)	32.76	31.2	(0.53)	0.99	(0.28)	-1.63	(-0.51)
Mean years schooling (2005)	6.26	6.19	(0.32)	0.04	(0.15)	0.1	(0.36)
Infant mortality (2005)	22.54	22.26	(0.22)	0.14	(0.10)	0.35	(0.27)
HH w/o access to sewage (2005)	8.51	8.44	(0.05)	0.24	(0.15)	0.43	(0.36)
HH w/o access to water (2005)	16.14	18.22	(-0.62)	-0.94	(-0.23)	-1.58	(-0.52)
Marginality index (2005)	-0.15	-0.12	(-0.23)	-0.06	(-0.31)	-0.09	(-0.49)
Detour length (km)	27.32	24.58	(0.14)	4.68	(0.16)	17.99	(0.85)
Road density (km/km^2)	0.15	0.13	(1.08)	0.01	(0.52)	0	(0.10)
Distance U.S. (km)	708.27	735.49	(-0.55)	-73.77	(-1.23)	-78.56	(-1.30)
Elevation (m)	1406.75	1380	(0.19)	-30.38	(-0.18)	-47.49	(-0.29)
Slope (degrees)	3.62	3.25	(0.89)	0.31	(0.58)	0.1	(0.25)
Surface area (km^2)	1787.36	725.37	(1.36)	1488.74	(1.46)	1089.61	(1.29)
Average min. temperature, C	11.76	12.23	(-0.57)	-0.39	(-0.38)	-0.45	(-0.47)
Average max. temperature, C	26.37	26.64	(-0.45)	-0.22	(-0.30)	-0.13	(-0.21)
Average precipitation, cm	115.16	105.2	(0.82)	10.87	(0.79)	2.1	(0.16)
Observations	70	82		430		430	

Notes: Data on population, population density, mean years of schooling, and migrants per capita are from *II Conteo de Poblacion y Vivienda*, INEGI (National Institute of Statistics and Geography, 2005). Data on municipal tax collection are from *Sistema de Cuentas Municipales, INEGI.* Data on household access to sewage and water are from CONAPO (National Population Council) (2005). Data on malnutrition are from CONEVAL (National Council for Evaluating Social Development Policy), *Indice de Reazgo Social* (2005). Data on infant mortality are from PNUD Mexico (UN Development Program, 2005). The marginality index is from CONAPO (2005). Data on distance to the U.S. and other road network characteristics are from the author's own calculations. Electoral data are from Mexico Electoral-Banamex and electoral results published by the Electoral Tribunals of each state. The geographic characteristics are from Acemoglu and Dell (2009). Data on homicides (1990-2006) are from INEGI and data on drug trade-related violence are from confidential sources. Columns (1) through (5) examine these variables for municipalities with close elections. Column (6) and (7) examine the means of these variables for municipalities that border a municipality with a close election. Column (3) reports the t-statistic on the difference in means between municipalities where the PAN barely won and where they barely lost. Columns (4) and (6) report the coefficient on PAN win from equation (2) when the respective characteristic is used as the dependent variable, and columns (5) and (7) report the t-statistic on PAN win. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 2: Close PAN Elections and Violence

	Post inaug.	Lame duck	Pre election	No FE	No FE or controls	Linear	Quadratic		Cubic		Quartic	
						RD polynomial						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Probability of drug trade-related homicides												
PAN win						0.019		0.007		0.050		0.046
× lame duck						(0.058)		(0.059)		(0.088)		(0.090)
PAN win						0.147***		0.132***		0.204***		0.204***
× post-inaug.						(0.051)		(0.047)		(0.064)		(0.062)
PAN win	0.084***	0.005	0.014	0.093***	0.093**		0.127***		0.149***		0.179***	
	(0.027)	(0.030)	(0.013)	(0.026)	(0.043)		(0.036)		(0.046)		(0.060)	
R-squared	0.648	0.686	0.868	0.576	0.024	0.237	0.652	0.240	0.653	0.244	0.655	0.244
Clusters						152		152		152		152
Observations	430	430	430	430	430	1,960	430	1,960	430	1,960	430	1,960
Panel B: Drug trade-related homicide rate												
PAN win						0.026		0.018		0.068*		0.068*
× lame duck						(0.025)		(0.025)		(0.038)		(0.038)
PAN win						0.089**		0.088**		0.107**		0.103**
× post-inaug.						(0.038)		(0.038)		(0.041)		(0.040)
PAN win	0.046**	0.007	0.005	0.044**	0.047**		0.066**		0.096***		0.090**	
	(0.020)	(0.023)	(0.005)	(0.020)	(0.023)		(0.029)		(0.037)		(0.040)	
R-squared	0.370	0.250	0.643	0.246	0.021	0.219	0.374	0.220	0.380	0.222	0.386	0.223
Clusters						152		152		152		152
Observations	430	430	430	430	430	1,960	430	1,960	430	1,960	430	1,960

Notes: In columns (1), (4), (5), (7), (9), and (11) the dependent variable is the average monthly homicide probability (Panel A) or rate (Panel B) in the post-inauguration period; in column (2) it is average homicides in the lame duck period, and in column (3) it is average homicides in the pre-election period. In columns (6), (8), (10), and (12), it is the homicide dummy (rate) in a given municipality-month. PAN win is a dummy equal to one if a PAN candidate won the election, lame duck is a dummy equal to one if the observation occurred between the election and inauguration of a new mayor, and post-inaug. is a dummy equal to one if the observation occurred after the inauguration of a new mayor. Columns (6), (8), (10), and (12) include a lame duck main effect, a post-inauguration main effect, month x state and municipality fixed effects, and interactions between the RD polynomial listed in the column headings and the lame duck and post-inauguration dummies. These columns limit the sample to municipalities with a vote spread of five percentage points or less. Columns (1) through (3), (7), (9), and (11) include state fixed effects and controls for baseline characteristics, estimated separately on either side of the PAN win-loss threshold. The coefficients in columns (1) through (5), (7), (9), and (11) are estimated using local regression, with separated trends in vote spread estimated on either side of the PAN win-loss threshold. Robust standard errors, clustered by municipality in columns (6), (8), (10), and (12), are in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 3: Local Politics in More Detail

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Elections involving PAN				Alternative samples	
	Baseline	PAN Incumbent	PAN Governor	PRI Opponent	PRI v. PRD	Any alternation	All muns.
PAN win	0.084***	0.067**	0.089***	0.069**			0.148
	(0.026)	(0.028)	(0.028)	(0.029)			(0.250)
PAN win × PAN Incumbent		0.056					
		(0.040)					
PAN win × PAN Governor			-0.037				
			(0.079)				
PAN win × PRI opponent				0.021			
				(0.032)			
PRI win					0.050		
					(0.035)		
Alternate						0.012	
						(0.018)	
R-squared	0.648	0.648	0.648	0.649	0.571	0.554	0.577
Observations	430	430	430	430	259	780	1,286

Notes: The dependent variable in all columns is the average probability that a drug trade-related homicide occurred in a given municipality-month during the post-inauguration period. PAN win is a dummy equal to one if a PAN candidate won the election, PRI win is a dummy equal to one if a PRI candidate won the election, Alternate is a dummy equal to one for any alternation of the political party controlling the mayorship, Pan Incumbent is a dummy equal to 1 if the municipality had a PAN incumbent, and PRI opponent is a dummy equal to one if the PAN candidate faced a PRI opponent. Columns (1) through (5) are estimated using local regression, with separate trends in vote spread estimated on either side of the PAN win-loss threshold. All columns included state fixed effects, as well as baseline controls estimated separately on either side of the PAN win-loss threshold. Column (2) also includes interactions between the vote spread terms and the PAN incumbent dummy, and Column (3) includes interactions between the vote spread terms and the PRI opponent dummy. Columns (1) through (3) limit the sample to municipalities where a PAN candidate was the winner or runner-up, Column (4) limits the sample to municipalities with a close election between PRI and PRD candidates, and Column (5) includes all municipalities with a close election, regardless of the political parties involved. Column (6) includes all elections where a PAN candidate was the winner or runner-up. Robust standard errors are in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 4: Trafficking Industrial Organization and Violence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent variable is drug trade-related homicides (probability or indicator)											
PAN win	0.084***		0.020		0.037		0.087***		0.132***		0.151***	
	(0.027)		(0.026)		(0.031)		(0.025)		(0.035)		(0.045)	
PAN win × borders rival			0.513***		0.268							
			(0.180)		(0.233)							
PAN win × borders allies			0.126*		0.172*							
			(0.071)		(0.095)							
PAN win × local gang			0.012		0.010							
			(0.032)		(0.045)							
PAN win × detour							0.070***		0.070***		0.070***	
							(0.022)		(0.021)		(0.022)	
PAN win × post		0.147***		0.123**		0.107**		0.134***		0.122***		0.169***
		(0.051)		(0.051)		(0.047)		(0.041)		(0.038)		(0.051)
PAN win × post × borders rival				0.401***		0.411***						
				(0.116)		(0.111)						
PAN win × post × borders allies				0.047		0.049						
				(0.102)		(0.098)						
PAN win × post × local gang				0.009		0.019						
				(0.024)		(0.026)						
PAN win × post × detour								0.150***		0.148***		0.144***
								(0.024)		(0.022)		(0.021)
Vote spread terms	linear	linear	linear	linear	quad.	quad.	linear	linear	quad.	quad.	cubic	cubic
R-squared	0.648	0.247	0.633	0.271	0.646	0.274	0.671	0.279	0.675	0.282	0.676	0.283
Clusters		152		152		152		152		152		152
Observations	430	1,672	430	1,672	430	1,672	430	1,672	430	1,672	430	1,672
Borders rival effect			0.533***	0.524***	0.306	0.518***						
			(0.174)	(0.131)	(0.226)	(0.122)						
Borders allies effect			0.146**	0.169*	0.209**	0.157*						
			(0.069)	(0.092)	(0.090)	(0.091)						
Local gang effect			0.032	0.132**	0.047	0.127**						
			(0.028)	(0.052)	(0.040)	(0.051)						

Notes: In columns (1), (3), (5), (7), (9), and (11), the dependent variable is the average probability that a drug trade-related homicide occurred in a given municipality-month during the post-inauguration period. In columns (2), (4), (6), (8), (10), and (12), the dependent variable is a dummy variable equal to one if a drug trade-related homicide occurred in a given municipality-month. Borders rival is a dummy equal to one if the municipality is controlled by a major DTO and borders territory controlled by a rival DTO, borders allies is a dummy equal to one if the municipality is controlled by a major DTO and does not border territory controlled by a rival, and local gang is a dummy equal to one if the municipality is controlled by a local drug gang. No known drug trade presence is the omitted category. Detour is the standardized increase in total trafficking costs when the municipality's roads are removed from the trafficking network. Post is a dummy equal to one if the observation occurs during the post-inauguration period. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 5: The Diversion of Drug Traffic

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample		Limited Sample		Placebo Paths		Full Sample	
	Domestic illicit drug confiscations						Cocaine confiscations	
	Dummy	Value	Dummy	Value	Dummy	Value	Dummy	Value
Panel A: Shortest Paths								
Predicted	0.016***	0.170***	0.015**	0.162**	0.004	0.038	0.004	0.027
routes dummy	(0.005)	(0.050)	(0.006)	(0.063)	(0.004)	(0.038)	(0.004)	(0.020)
Panel B: Model with Congestion Costs								
Predicted	0.015***	0.178***	0.013**	0.159**	0.006	0.036	-0.002	0.014
routes dummy	(0.005)	(0.059)	(0.006)	(0.064)	(0.006)	(0.069)	(0.004)	(0.023)
State x month FE	yes	yes	yes	yes	yes	yes	yes	yes
Municipality FE	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.42	0.47	0.42	0.47	0.42	0.47	0.37	0.37
Municipalities	1869	1869	1574	1574	1869	1869	1869	1869
Observations	69,153	69,153	58,238	58,238	69,153	69,153	69,153	69,153
Mean dep. var.	0.053	0.589	0.055	0.613	0.053	0.589	0.046	0.163

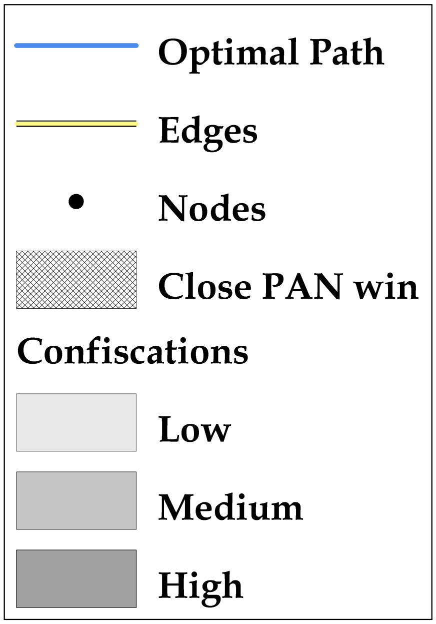
Notes: The dependent variable in columns (1), (3), and (5) is a dummy equal to 1 if domestic illicit drug confiscations are made in a given municipality-month; the dependent variable in columns (2), (4), and (6) is the log value of domestic illicit drug confiscations (or 0 if no confiscations are made); the dependent variable in column (7) is a dummy equal to 1 if cocaine confiscations are made in a given municipality-month; and the dependent variable in column (8) is the log value of confiscated cocaine (or 0 if no confiscations are made). Columns (5) and (6) use the placebo network, as described in the text. Columns (3) and (4) limit the sample to municipalities that do not border a municipality that has experienced a close PAN victory. Panel A predicts trafficking routes using the shortest paths model, and Panel B uses the model with congestion costs. All columns include month x state and municipality fixed effects. Standard errors clustered by municipality and month x state are reported in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 6: Violence Spillovers

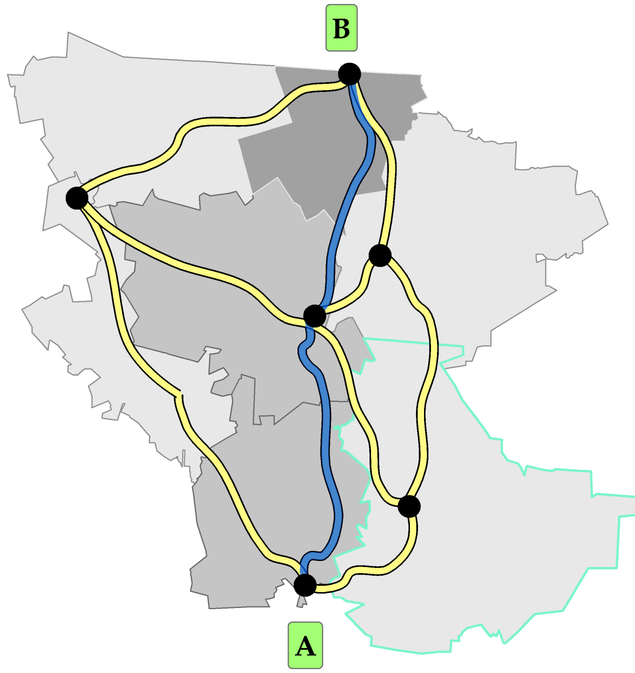
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full Sample		Full Sample		Limited Sample		Full Sample	Placebo Paths	
			Drug-related homicide				Non-drug homicide	Drug-related homicide	
	dummy	dummy	rate	rate	dummy	rate	rate	dummy	rate
Panel A: Shortest Paths									
Predicted routes dummy	0.013***		0.021*		0.006	0.010	0.017	0.002	0.002
	(0.005)		(0.011)		(0.006)	(0.011)	(0.014)	(0.003)	(0.011)
One route		0.014*		0.020*					
		(0.007)		(0.011)					
More than one route		0.012		0.021					
		(0.008)		(0.017)					
Panel B: Model with Congestion Costs									
Predicted routes dummy	0.015***		0.022		0.018***	0.029	-0.000	0.003	-0.011
	(0.005)		(0.019)		(0.006)	(0.025)	(0.007)	(0.006)	(0.013)
One route		0.008		0.003					
		(0.006)		(0.013)					
More than one route		0.019***		0.035					
		(0.007)		(0.025)					
State x month FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Municipality FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.36	0.36	0.10	0.10	0.35	0.09	0.07	0.36	0.10
Municipalities	1869	1869	1869	1869	1574	1574	1869	1869	1869
Observations	69,153	69,153	69,153	69,153	58,238	58,238	69,153	69,153	69,153
Mean dep.var.	0.044	0.028	0.044	0.028	0.045	0.026	0.117	0.044	0.028

Notes: The dependent variable in columns (1), (2), (5) and (8) is a dummy equal to 1 if a drug trade-related homicide occurred in a given municipality-month; the dependent variable in columns (3), (4), (6), and (9) is the drug trade-related homicide rate per 10,000 municipal inhabitants, and the dependent variable in column (7) is the non-drug trade-related homicide rate per 10,000 municipal inhabitants. Columns (8) and (9) use the placebo network, as described in the text. Columns (5) and (6) limit the sample to municipalities that do not border a municipality that has experienced a close PAN victory. All columns include month x state and municipality fixed effects. Standard errors clustered by municipality and month x state are reported in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%.

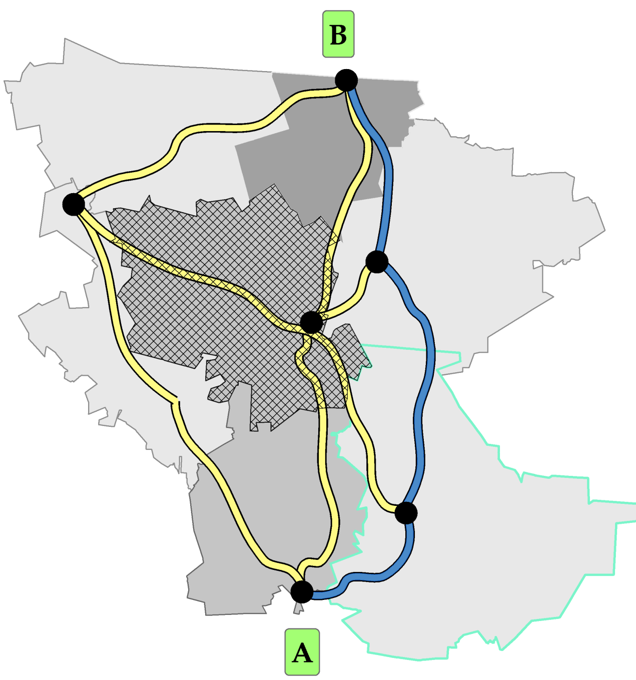
Figure 1: Illustration of Spillovers Methodology



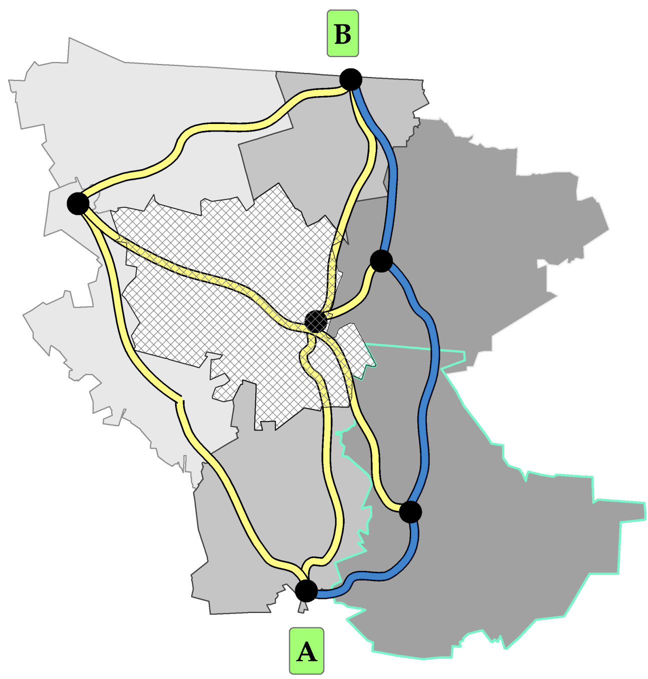
(a) Legend



(b) Basic environment

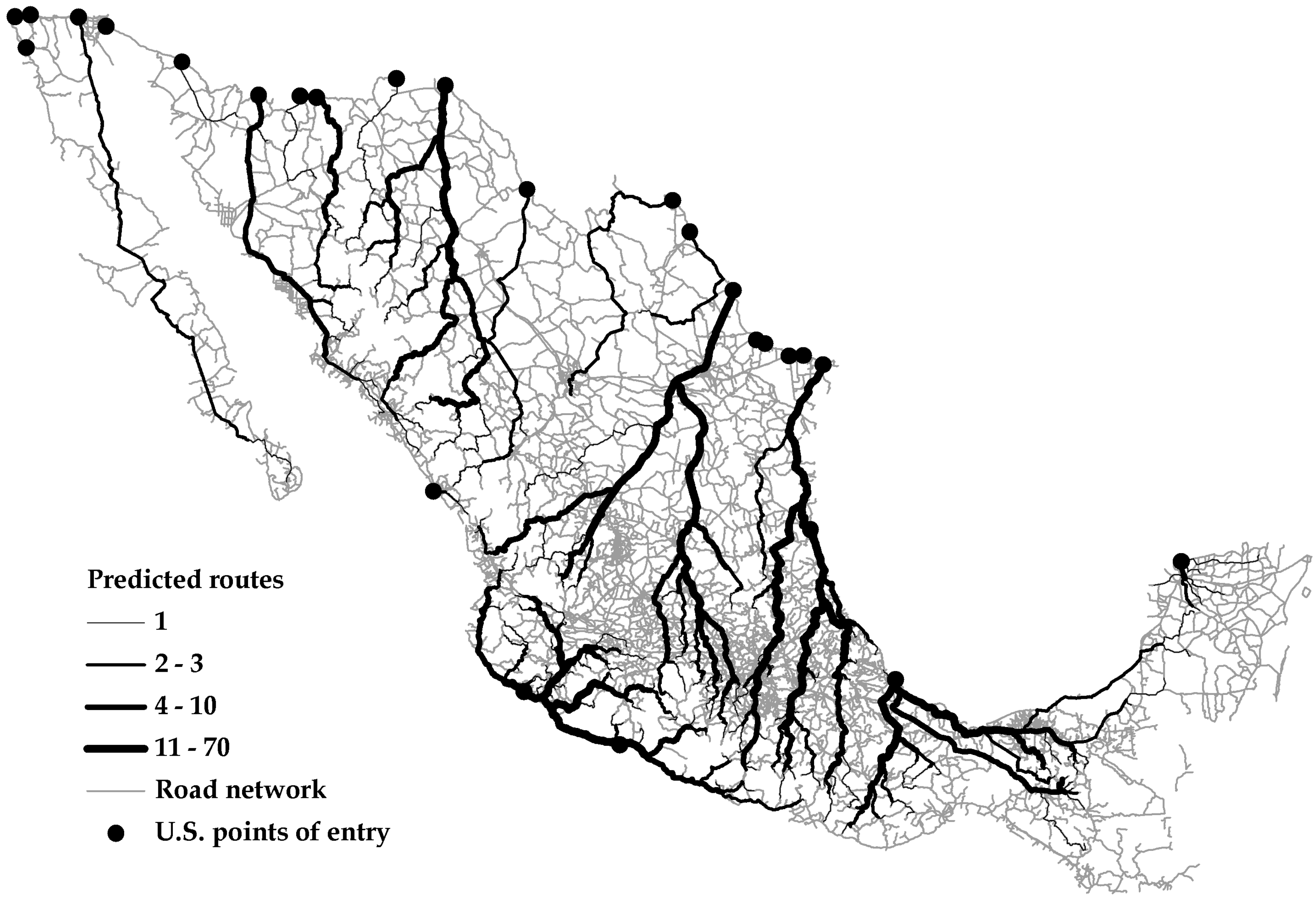


(c) Close PAN victory increases costs; routes change



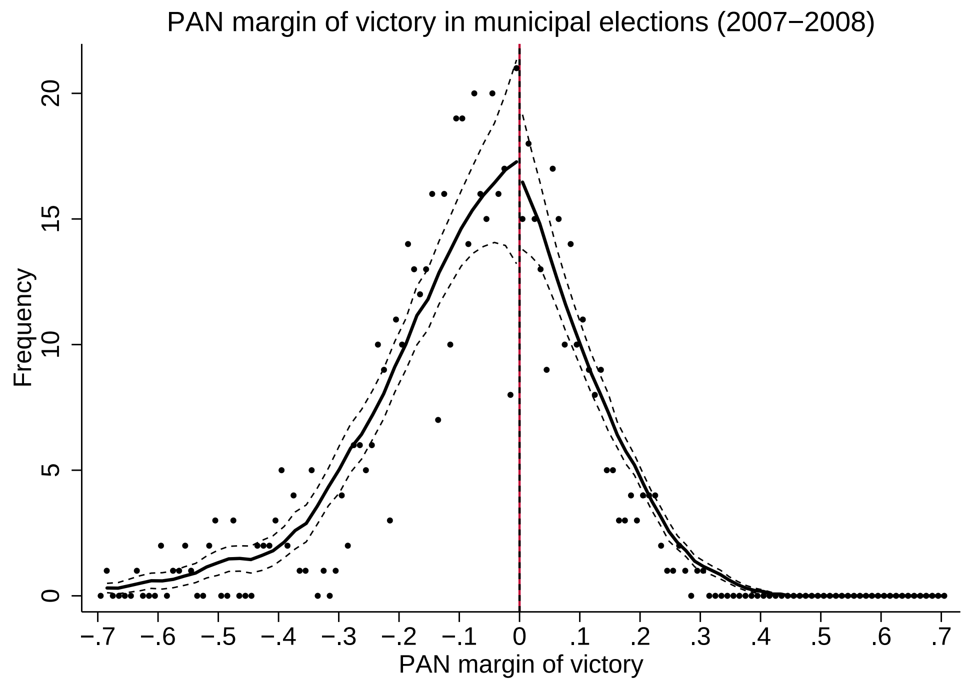
(d) Do confiscation patterns also change?

Figure 2: Road Network and Predicted Trafficking Routes



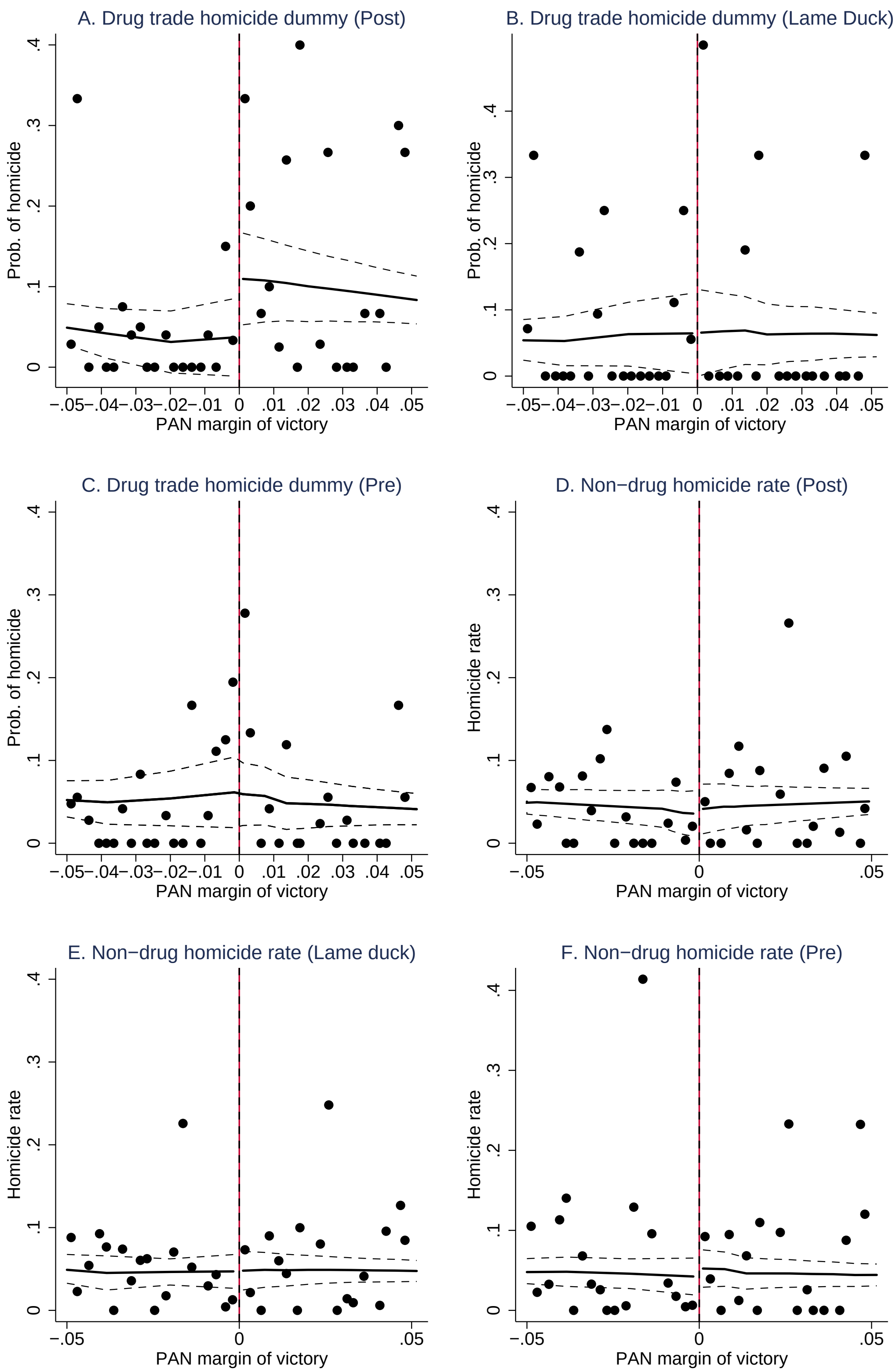
Notes: The least cost routes plotted in this figure are predicted using the network model with congestion costs.

Figure 3: RD Results: Close PAN Victories and Violence



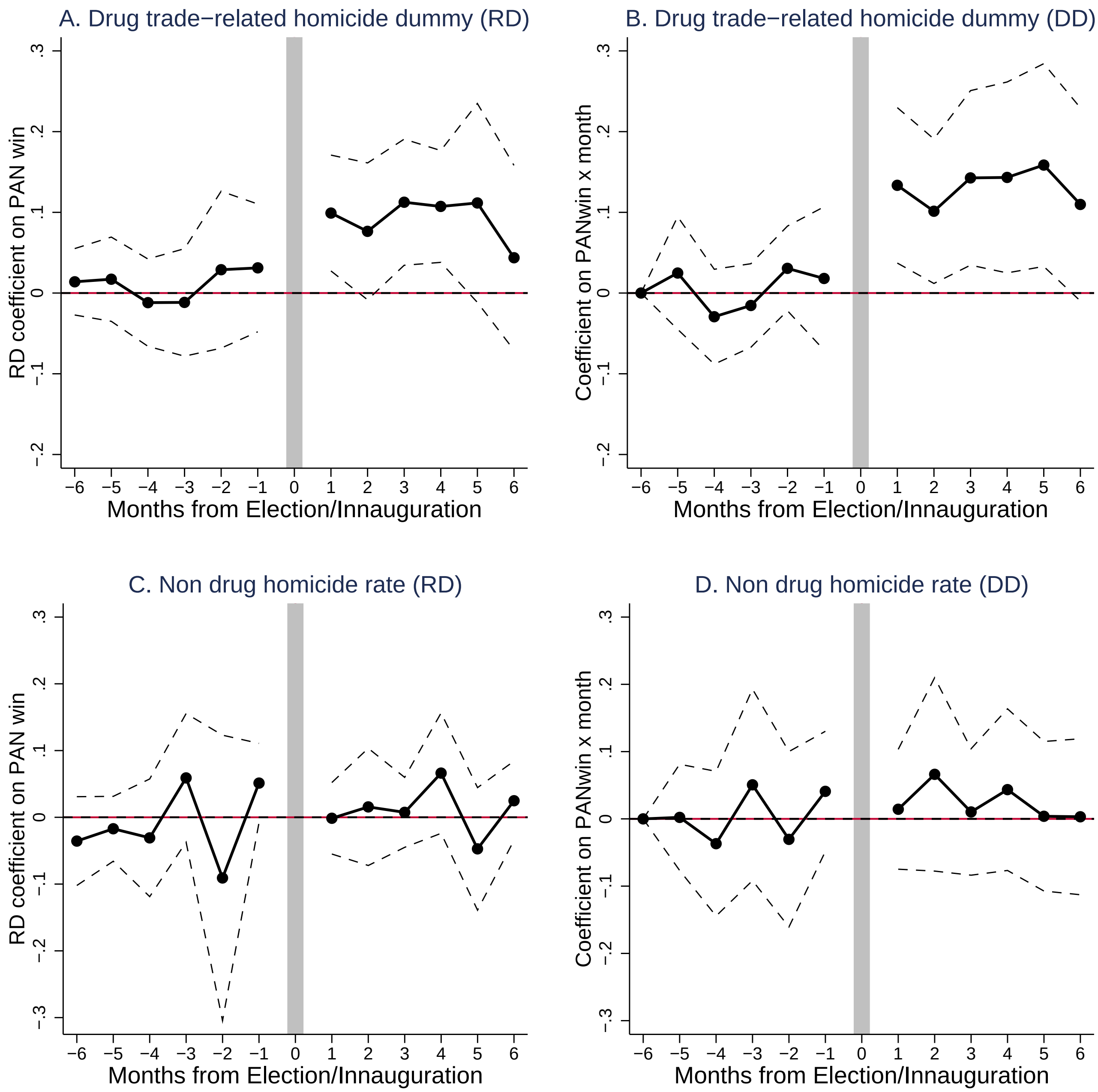
Notes: This figure shows the frequency of mayoral elections (2007-2008) in one percentage point vote spread bins. The solid line plots predicted values from a local linear regression of frequency on vote spread, with separate vote spread trends estimated on either side of the PAN win-loss threshold. The dashed lines show 95% confidence intervals. The bandwidth is chosen using the Imbens-Kalyanaraman bandwidth selection rule (2009), and a rectangular kernel is used.

Figure 4: RD Results: Close PAN Victories and Violence



Notes: This figure plots violence measures against the PAN margin of victory, with a negative margin indicating a PAN loss. Each point represents the average value of the outcome in vote spread bins of width 0.0025. The solid line plots predicted values from a local linear regression, with separate vote spread trends estimated on either side of the PAN win-loss threshold. The dashed lines show 95% confidence intervals. The bandwidth is chosen using the Imbens-Kalyanaraman bandwidth selection rule (2009).

Figure 5: Estimates by Month



Notes: Panels A and C plot the RD coefficients on PAN win from equation (2), estimated separately for each month prior to the election and following the inauguration of new authorities. Panels B and D plot the γ_τ coefficients from equation (3). The dashed lines plot 95% confidence intervals.