Trafficking Networks and the Mexican Drug War* (Job Market Paper)

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Abstract: Drug trade-related violence has escalated dramatically in Mexico during the past five years, claiming 40,000 lives and raising concerns about the capacity of the Mexican state to monopolize violence. 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 accurately predicts diversion of drug traffic following close PAN victories. It does this 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. Moreover, female labor force participation and informal sector wages fall, corroborating qualitative evidence that traffickers extort informal sector producers. 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.

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1 Introduction

Drug trade-related violence has escalated dramatically in Mexico during the past five years, claiming 40,000 lives and raising concerns about the capacity of the Mexican state to monopolize violence. Recent years have also witnessed large scale efforts spearheaded by Mexico's conservative National Action Party (PAN) to combat drug trafficking. 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.

Given that transporting drugs to the United States is the primary economic activity of Mexican drug trafficking organizations, the study begins by specifying a network model of drug trafficking. This model is used as an empirical tool for analyzing the direct and spillover effects of local policy towards the drug trade. Its central ingredient is the reasonable assumption that traffickers' objective is to minimize the costs incurred in trafficking drugs from producing municipalities in Mexico across the Mexican road network to U.S. points of entry. 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 simple approach, the study specifies and estimates a richer version of the model that imposes congestion costs when trafficking routes coincide.

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 tests whether the outcomes of close mayoral elections involving the National Action Party (PAN), which has spearheaded Mexico's war on drug trafficking, affect drug trade-related violence. It also explores mechanisms that could lead violence to increase in response to crackdowns initiated by PAN mayors. The analysis focuses on violence because it is relatively well-measured and central to debates about Mexican drug trafficking policy. Second, the study examines whether drug trafficking routes are diverted to other municipalities following close PAN victories and tests whether the diversion of drug traffic is accompanied by violence and economic spillover effects. Finally, the study uses the trafficking model and estimated spillover effects to examine the allocation of law enforcement resources.

The PAN's role in spearheading the war on drug trafficking, as well as qualitative evidence that PAN mayors have contributed to these efforts, motivate the use of close mayoral elections to identify the direct and spillover effects of government policy towards the drug trade. Regression discontinuity (RD) estimates exploiting the outcomes of these 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.[1] This is a large effect, given that six percent of municipality-months in the sample experienced a drug trade-related homicide. The validity of the identification approach is supported by the fact that the outcomes of close elections are uncorrelated with violence and a large number of other municipal characteristics measured before the elections occurred. 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 it 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 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, but by weakening the incumbent criminal group they also reduce the costs of taking control of a municipality. Controlling the municipality could offer substantial rents from trafficking and a variety of other criminal activities once the crackdown subsides.

[1] See Lee, Moretti, and Butler (2004) for a pioneering example of a regression discontinuity design exploiting close elections.

The paper'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 roubstly predicts the diversion of drug traffic following PAN crackdowns. 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, this generates month-to-month plausibly exogenous variation in predicted routes from producing municipalities to the U.S. This variation can be compared to variation in monthly panel data on actual illicit drug confiscations and other outcomes. This approach is illustrated in Figure 1. I show that 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.

I then use the simulated method of moments to estimate a richer model that includes 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 changes in confiscations within municipalities over time, with the presence of a predicted drug trafficking route increasing the value of illicit drug confiscations in a given municipality-month by around 19.5 percent. The relationship between predicted routes and confiscations is robust to varying the form of the congestion costs, to imposing a variety of costs for trafficking drugs through a municipality that has experienced a close PAN victory, to dropping municipalities from the sample that are located near municipalities that have experienced a close PAN victory, and to using different measures of illicit drug confiscations. Placebo checks also support the

[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).

validity of the approach.

When a municipality acquires a predicted trafficking route, regardless of whether the simple or richer model is used 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. When routes are predicted using the model with congestion, the violence spillovers are concentrated in municipalities where two or more routes coincide. Moreover, when a municipality acquires a predicted route, wages earned by adult men in the informal sector fall by around 2.5 percent and female labor force participation declines by around one percentage point, relative to a baseline participation rate of 51 percent. Formal sector wages and male labor force participation are not affected. The economic spillovers are noisily estimated and thus should be interpreted with caution. Nevertheless, they are consistent with qualitative evidence discussed in Section 2 that drug trafficking organizations extort informal sector producers via protection rackets.

While high rates of violence and the flexibility of trafficking operations pose major challenges to state efforts to combat the drug trade, this study's results indicate that crackdowns increase trafficking costs, at least in the short run. Moreover, violence tends to respond in predictable ways. The study's third set of results uses the trafficking model and estimated spillover effects to examine how scarce law enforcement resources can be allocated so as to increase costs to traffickers as much as possible. I also discuss how the violence response to this policy may be reduced. Decreasing the profits of traffickers is one important goal of drug policy because it may serve as a mechanism for achieving broader policy aims (Shirk, 2011). In making the case for why combating drug trafficking is important for Mexico's long-term interests, President Felipe Calderón argued that organized criminals had infiltrated public institutions to such an extent that challenging trafficking groups was imperative for protecting national security and preventing institutional deterioration. 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 public security had yet to be realized. Moving forward, empirical examination of whether crackdowns have led to longer-term changes in governance and security outcomes, both directly and through spillover effects, will be important for evaluating the broader effectiveness of Mexico's policies towards drug trafficking.

The next section provides an overview of Mexican drug trafficking and state policies towards the drug trade, and Section 3 develops a simple network model of drug trafficking. Section 4 examines whether the outcomes of close elections involving the PAN influence drug trade-related violence and explores mechanisms linking the outcomes of these elections to violence. Section 5 documents that close PAN mayoral victories divert drug traffic elsewhere. It also estimates a richer version of the trafficking model and explores whether PAN crackdowns exert violence and economic spillover effects. Section 6 utilizes the trafficking model and estimated spillover effects to examine the efficient allocation of law enforcement resources. Finally, Section 7 offers concluding remarks.

2 Background

Mexican drug traffickers dominate the wholesale illicit drug market in the United States. 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 on drug producing regions, obtained from confidential sources, document that fourteen percent of Mexico's municipalities regularly produce opium poppy seed (used to make heroin) or cannabis. Moreover, Mexico serves as a major transhipment hub for cocaine, with 60 to 90 percent of the cocaine consumed in the U.S. transiting through Mexico (U.S. Drug Enforcement Agency, 2011).

The U.S. State Department estimates that wholesale earnings of Mexican drug traffickers in U.S. markets range from $13.6 billion to $48.4 billion annually.[3] While the margin of error on this estimate is large, there is consensus that the U.S. market provides substantially more revenue than Mexico's domestic illicit drug market, which is worth an estimated $560 million annually (Secretaría de Seguridad Pública, 2010). Data on drug addiction also emphasize the importance of the U.S. illicit drug market. 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).

At the beginning of this study's sample period, there were six major drug trafficking organizations operating in Mexico, as well as many local gangs. 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 Mexico's 320 drug producing municipalities were controlled by a major drug trafficking organization in 2008, whereas the remaining 51 percent were controlled by local gangs. Local groups typically ally with more sophisticated trafficking organizations to transport their drugs to the U.S.

While the term 'cartel' is used colloquially to refer to Mexican drug trafficking organizations, these competing groups do not collude to reduce illicit drug production or to set

[3]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.

the price of illicit drugs. As documented in detail by Eduardo Guerrero (2011, p. 106-108), alliances between drug trafficking organizations have been highly unstable during the past five years. Moreover, the number of major trafficking organizations in Mexico expanded from 6 in 2007 to 16 by mid-2011, with cells breaking away from the larger organizations over disputes about leadership and operational issues (Guerrero, 2011, p. 10). Within drug trafficking organizations, many decisions about day-to-day operations are decentralized. Decisionmaking by semi-independent local cells ensures that no single player will be able to reveal extensive information if he or she is captured by authorities. Moreover, higher level traffickers often do not have the capacity to make heavily armed local traffickers or producers follow orders that are not in their individual interest.

While the U.S. illicit drug market provides the main source of revenues for Mexican drug trafficking organizations, they are diversified into a host of other illicit activities, including domestic drug sales, protection rackets, kidnapping, human smuggling, prostitution, oil and fuel theft, money laundering, weapons trafficking, and auto theft (Guerrero, 2011, p. 10). Drug trafficking organizations have substantially expanded their operations in some of these activities in recent years (Rios, 2011a). Most notably, protection rackets involving the general population have increased substantially, with complaints to authorities tripling between 2004 and 2009 (Secretariado Ejecutivo del Sistema Nacional de Seguridad Pública, 2011). In a recent 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* reporting that they had been extorted by traffickers. Such activities affect the lives of many citizens who are unaffiliated with the drug trade, and as of 2011, public opinion surveys found that public security was more likely to be chosen as the largest problem facing the country than concerns about the economy.

Historically, Mexican politics were dominated by a single party, the PRI (Institutionalized Revolutionary Party). Both local and federal authorities took a passive stance towards drug trafficking, and there were a number of well-documented instances in which officials engaged in drug trade-related corruption (see for example Shannon, 1988). While the Mexican federal government periodically cracked down on drug trafficking, these operations were limited in size and scope.[4] The PRI's dominance began to erode in the 1990s, and the first opposition president was elected from the National Action Party (PAN) in 2000. Today Mexico is a competitive multi-party democracy.

Government efforts to combat the drug trade have increased substantially in recent years.

[4]Notable examples include Operation Condor in the 1970s to eradicate illicit drug crops in northern Mexico and the deployment of federal troops to Nuevo Laredo, Tamaulipas by PAN president Vicente Fox in the early 2000s.

Soon after taking office in December 2006, PAN president Felipe Calderón deployed 6,500 federal troops to the state of Michoacan to combat drug trade-related violence. The government's operations against drug trafficking have continued to increase since this time, with approximately 45,000 troops involved by 2011. Military and federal police operations have been a centerpiece of Calderón's administration, and major judicial reforms were also legislated in 2008. However, the criminal justice system remains weak, and it is estimated that only 2% of felony crimes are prosecuted (Shirk, 2011).

Since the start of Calderón's presidency in December 2006, violence has increased dramatically in Mexico. Over 40,000 people were killed by drug trade-related violence between 2007 and mid-2011, and drug trade-related violence has increased by at least 30 percent every year during this period (Rios, 2011b). More than 85 percent of the violence consists of people involved in the drug trade killing each other. Whether or not the increase in violence has been caused by state policy has been controversial, with political scientists taking both sides of the debate (see Shirk, 2011, p. 8 for a discussion of this controversy). Some have used qualitative and descriptive evidence to argue that the state's policies have ignited conflicts between traffickers, leading to the large increase in violence in recent years (see Guerrero, 2011 for a detailed discussion), while others argue 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). This study presents causal evidence linking crackdowns to large increases in drug trade-related violence.

Local authorities command the majority of Mexico's law enforcement officers. In total, there are 2,139 independent state, local, and federal police agencies in Mexico, 2038 of which are municipal police agencies, and 90% of Mexico's approximately 500,000 police officers are under the command of state and municipal authorities (Guerrero, 2011, p. 20). Mayors, who are elected every three years at different times in each of Mexico's 31 states and Federal District, name the municipal police chief and set policies regarding police conduct. Municipal police have a limited mandate, focusing on automobile traffic violations and minor disruptions to public order. It is rare for them to confiscate illicit drugs, and they do not have the training or weaponry typically required to make high level drug arrests. Because their main activities involve patrolling the local environment, municipal police can however serve as critical sources of information for military and federal police attacks on drug trafficking operations. For the same reasons, municipal police are also valuable allies for organized criminals, who need information on who is passing through the municipalities they control so that they can protect local criminal operations and anticipate attacks by their rivals and by federal authorities.[5] The importance of municipal police is reflected by the fact that they

[5]For example, in a recent meeting on national security, Mexican president Felipe Calderón argued: "The

form the largest group of public servants killed by drug trade-related violence (Guerrero, 2011).

Qualitative evidence indicates that operations involving the federal police and military have tended to be most effective when the relevant local authorities are aligned with the party controlling the federal government (Guerrero, 2011, p. 70). 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. Qualitative evidence also suggests that PAN mayors and governors are more likely to request assistance from the federal police.[6]

There are several potential explanations for these patterns. Authorities from the same party may coordinate law enforcement operations 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] While disentangling these explanations is infeasible given data constraints and the inherent empirical challenges in separately identifying mechanisms, these plausible channels motivate this study's focus on close elections involving the PAN.

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

military report that when they enter a city, they tune into the frequency of the municipal police radio and hear them reporting to the criminals every step they [the military] take. 'And right now they are on this avenue arriving at the traffic light on that corner, and they have six trucks and bring this many weapons.' And these municipal police patrols attempt to block their [the military's] access" (*El Pais*, August 26, 2010, translation mine.

[6]Disaggregated data on federal police assignments and requests by mayors for federal police assistance are not made available to researchers.

[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.

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 large 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. Hence, 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 accurately 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

[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.

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 strategic interactions are 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 typically enters Mexico via fishing vessels and go-fast boats that transport bulk shipments from producing countries in the Andean region to Mexico (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 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.

I turn now to an examination of the direct and spillover effects of close PAN victories. The shortest paths predicted by the trafficking model are used to examine why PAN victories lead to large increases in violence and to locate violence and economic spillover effects. The shortest paths model provides an intuitive starting point for this analysis, and later in the

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

paper I enrich the model to include additional costs and interactions between traffickers.

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 involving the National Action Party (PAN) - which has spearheaded the war on drug trafficking - affect violence in the municipalities experiencing these close elections. The analysis focuses on violence because it is relatively well-measured and central to debates about Mexican drug trafficking policy. While disaggregated data on mayoral requests for federal police as well as the allocation of the military and federal police are not made available to researchers, the qualitative evidence discussed in Section 2 suggests that PAN mayors are more likely to crack down on the drug trade by enlisting the assistance of federal law enforcement and coordinating operations with them.

This section first describes the data and provides a graphical analysis of the relationship between violence and the outcomes of close elections. It then explores the robustness of this relationship and finally uses measures of the industrial organization of drug trafficking to explore mechanisms linking the outcomes of close elections to violence. To the extent that local crackdowns incentivize traffickers to relocate some of their operations, PAN victories could also exert spillover effects. These 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 In-

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

stitute 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 and graphical analysis

I now outline the study's empirical approach for estimating the direct effects of close PAN victories on violence and also provide a graphical analysis of the relationship between local politics and violence. I first analyze cross-sectional violence measures using standard non-parametric regression discontinuity methods (as described in Imbens and Lemieux, 2008), and then exploit the panel variation in the violence data by examining a specification that combines regression discontinuity and differences-in-differences. These approaches yield similar estimates.

In order to perform the regression discontinuity analysis, I restrict the data to a small window around the PAN win-loss threshold, so that only municipalities with a narrow vote spread between the winner and runner-up contribute to the estimate of the discontinuity. I choose this bandwidth using the Imbens-Kalyanaraman bandwidth selection rule (2009).[11] I then estimate a local linear regression using a triangular kernel, which ensures that the weight on each observation decays with the distance from the threshold. Specifically, I estimate the following regression model within the bandwidth:

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

where y_{ms} is the outcome of interest in municipality m in state s. $PANwin_{ms}$ is an indicator

[11] Results (available upon request) are robust to using a variety of different bandwidths.

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 controls measured prior to the sample period. While controls are not necessary for identification, their inclusion improves the precision of the estimates. The sample is restricted to elections where the PAN won or came in second.

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, and *spread* denote the PAN margin of victory, 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.

To assess the plausibility of this assumption, Table 1 compares municipal crime, political, economic, demographic, road network, and geographic characteristics in municipalities where the PAN barely lost to those in municipalities where they barely won. Crime characteristics include the average monthly drug-trade related homicide rate between December of 2006 (when these data were first collected) through June of 2007 (when the first authorities elected during the sample period were inaugurated), as well as the average probability that a drug trade-related homicide occurred in a given month during this period. They also include police-criminal confrontation deaths per 100,000 inhabitants (Dec. 2006 - Jun. 2007), the average probability that police criminal-confrontation deaths occurred, and the long-run average municipal homicide rate (1990-2006). Political characteristics explored are municipal tax collection per capita (2005), municipal taxes per dollar of income (2005), dummies for the party of the mayoral incumbent, the percentage of electoral cycles between 1976 and 2006 in which the party of the mayor alternated, and a dummy equal to 1 if the PRI always controlled the mayorship between 1976 and 2006. Demographic characteristics are population (2005), population density (2005), and migrants per capita (2005). Economic characteristics include income per capita (2005), the municipal Gini index (2005), migrants per capita (2005), malnutrition (2005), mean years of schooling (2005), infant mortality (2005), percent of households without access to sewage (2005), percent of households without access to water (2005), and the municipal marginality index (2005).[12] Road network characteristics are the total detour length in kilometers required for the shortest path drug routes to circumvent the municipality, total length of roads in the municipality (2005), road density, and distance of the municipality to the U.S. border. Finally, the geographic characteristics are average

[12]The marginality index incorporates information on literacy; primary school completion rates; access to electricity, sewage, and running water; household overcrowding; construction materials used in households; municipal population in rural areas; and household income.

municipal elevation, slope, surface area, low temperature (1950-2000), high temperature (1950-2000), and precipitation (1950-2000). Sources for these variables are listed in the notes to Table 1.

Column (1) of Table 1 reports the mean value for each variable in municipalities where the PAN barely lost, column (2) does the same for municipalities where the PAN barley won, and column (3) reports the t-statistics on the difference in means. The sample is limited to elections with a vote spread between the winner and the runner-up of five percentage points or less. In no case are there statistically significant differences between municipalities where the PAN lost and municipalities where they won.[13] Moreover, I run the local linear regression specification given in equation (2) using each of the baseline characteristics as the dependent variable.[14] The coefficient on PAN win is reported in column (4) and the t-statistic on PAN win is reported in column (5). The coefficients on PAN win estimated by local linear regression tend to be small and in no case are they statistically different from zero. Overall, this evidence strongly suggests that municipalities where the PAN barely lost are a valid control group for municipalities where they barely won.

Identification also requires the absence of selective sorting around the PAN win-loss threshold. This assumption would be violated, for example, if PAN candidates in municipalities with a different drug trafficking trajectory could rig elections in their favor. While there are many historical examples of electoral fraud in Mexico, the political system has become dramatically more open since the early 1990s and genuine legal recourse exists in the event of concerns about electoral fraud. The balancing of the sample on the crime pre-characteristics, the electoral variables, and the many other characteristics in Table 1 indicates that rigged elections are unlikely to drive the results.

Due to space constraints, I focus on the probability that drug trade-related homicides occur in a given month in the graphical analysis, and later Table 2 documents that the results are robust to instead using the drug trade-related homicide rate per 10,000 municipal inhabitants.[15] Recall that drug trade-related homicides are those in which at least one party is involved in the drug trade. In over 85 percent of these homicides, both the aggressor and victim are involved in the drug trade. While a few municipalities always experience drug trade-related homicides, there is considerable variation in the extensive margin of violence.

The six panels in Figure 3 plot violence measures against the PAN margin of victory,

[13]Results are similar if the vote spread is limited to three or seven percentage points instead.

[14]State fixed effects are omitted to make the specification analogous to the difference in means reported in column (3). Results are similar when state fixed effects are included, and in no case is there a statistically significant discontinuity.

[15]It is not obvious that drug trade-related homicides should be normalized by municipal population, as drug trafficking activity is not necessarily proportional to population.

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).

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 in the post-inauguration period, there is a marked discontinuity in drug trade-related homicides at the threshold between a PAN loss and a PAN victory. The probability that a drug trade-related homicide occurs in a given month is around nine percentage points higher after a PAN mayor takes office than after a non-PAN mayor takes office. This can be compared to the sample average probability of six percent that a drug trade-related homicide occurs in a given month.

Next, Panel B examines drug trade-related homicides during the one to five month period between the election and inauguration of new authorities (the lame duck period), whose length varies by state. The figure documents that drug trade-related violence is similar in municipalities where the PAN barely won as compared to those where they barely lost. Panel C performs a placebo check, examining the average probability of a drug trade-related homicide during the six months prior to the election. There is no discontinuity at the PAN win-loss threshold, supporting the plausible exogeneity of close elections.

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 could systematically differ across municipalities. To explore whether the discontinuity in Panel A could simply reflect 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. 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 A1 in the online appendix). These results alleviate concerns that close elections simply affect the classification of 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 4 reports the coefficients on PAN win. State fixed effects and controls for the characteristics listed in Table 1 are included in order to increase the precision of the estimates.[16] Figure 4 plots the coefficients for the period lasting from six months prior to the election to six months following the inauguration of new authorities. The

[16]The coefficient magnitudes are very similar when the controls are excluded.

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. The dashed lines plot 95% confidence intervals.

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 PAN win coefficients document that before elections, drug trade-related homicides occurred with similar frequency in municipalities where the PAN would later barely lose versus in municipalities where they would barely win. These estimates support the validity of the identification strategy. Following the inauguration of new authorities, the PAN win coefficients become large, positive, and are statistically significant at the five or ten percent level in all periods except for six months following the inauguration.[17]

As an additional check on these results, I explore the relationship from an alternative perspective that exploits the full panel variation available in the monthly homicide series. Specifically, Panel B of Figure 4 plots the γ_τ coefficients from the following differences-in-differences specification against time:

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

where y_{mst} is the outcome in municipality m in state s in month t and $\{\zeta_\tau\}$ 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. $spread_{ms}$ is the margin of PAN victory, 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 between the winner and runner-up.[18] Panel B of Figure 4 shows that the magnitudes of the γ_τ coefficients are similar to the month-by-month cross-sectional RD estimates plotted in Panel A.

Panels C and D repeat the exercise for non-drug trade-related homicides. The month-

[17] When the post-period is extended to a year following the inauguration of new authorities, the coefficients are more volatile between seven and twelve months after the inauguration of new authorities (see Appendix Figure 1). Whether this is due to PAN authorities successfully deterring drug trafficking activity or results from these authorities becoming less tough on crime is not possible to establish definitively, but spillover results presented in the next section suggest that drug traffic continues to be diverted to other municipalities beyond the first six months that a PAN mayor has been in office.

[18] Results (available upon request) are similar when alternative windows around the PAN win-loss threshold are used.

by-month RD and the panel specification both show the absence of a discontinuity at the PAN win-loss threshold, before and after the inauguration of new authorities. Overall, the evidence in Figures 3 and 4 strongly support the hypothesis that government policy has exerted important effects on drug trade-related violence in Mexico.

4.3 Further 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. Before moving on to explore mechanisms, I examine this result in more detail.

Columns (1) through (3) of Table 2 report estimates from the local linear RD specification given by equation (2), estimating the magnitudes and standard errors of the discontinuities plotted in Figure 3. Panel A examines the probability of a drug trade-related homicide in a given month, and Panel B examines the drug trade-related homicide rate.[19] The specification includes state fixed effects and controls for the baseline characteristics listed in Table 1. The post-inauguration period extends to five months following the inauguration of new authorities (after which point the month-by-month analysis suggests that the violence effects start to decline somewhat), and the pre-election period extends to six months prior to the election.

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 reported in columns (2) and (3) 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 to excluding both the baseline controls and state fixed effects, as we would expect if close PAN victories are as if randomly assigned.[20]

Next, column (6) reports results from the following panel specification, which is analogous

[19] 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 Table A1 in the online appendix.

[20] The estimated effects for the lame duck and pre-election periods are also similar when state fixed effects and baseline controls are excluded.

to the differences-in-differences specification examined in the graphical analysis:

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

$LameDuck_{mst}$ is a dummy equal to one for all periods t between the election and inauguration of new authorities, $PostInnaug_{mst}$ is a dummy equal to one for all periods t in which the new municipal authorities have assumed power. All other variables are defined as in equation (3). 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.[21]

Column (6) reports estimates from equation (4) when a linear functional form is used for the RD polynomial. This specification estimates that the probability that at least one drug trade-related homicide occurs in a municipality in a given month is 14.7 percentage points higher after a PAN mayor takes office than after a non-PAN mayor takes office, and the monthly drug trade-related homicide rate is estimated to be 0.09 higher. The coefficients on lame duck × PAN win are substantially smaller than the post-inauguration × PAN win coefficients and are statistically insignificant. These results provide additional support for the robustness of the relationship between the outcomes of close elections and violence.

Local linear regression will not necessarily provide an unbiased estimate of the magnitude of the discontinuity if the true underlying functional form is not linear (Lee and Lemieux, 2009). While the RD figures suggest that the data are reasonably approximated by a linear functional form, columns (7) through (12) explore robustness to specifying the RD using a variety of functional forms. Columns (7), (9), and (11) estimate equation (2) using quadratic, cubic, and quartic vote spread terms, respectively (along with state fixed effects and baseline controls).[22] Columns (8), (10), and (12) estimate the panel specification using quadratic, cubic, and quartic RD polynomials, respectively. The estimated effects of close PAN victories on the probability of drug trade-related violence are large, positive, and statistically significant across specifications. The coefficients tend to increase somewhat in magnitude when higher order polynomials are used. The estimated impacts on the drug trade-related homicide rate are also large, positive, and statistically significant in all specifications except for the cross-sectional RD with a quartic polynomial.[23]

[21] Results are very similar when a seven or three percentage point vote spread is used instead.

[22] These specifications use the same bandwidth as the linear specification.

[23] Results (available upon request) are very similar when I use a semi-parametric, cross-sectional RD approach with various orders of RD polynomials, limiting the sample to municipalities with a five percentage point vote spread or less.

Deaths in police-drug trafficker confrontations and drug trade-related arrests are additional outcomes that we would expect to be affected by the outcomes of close elections. Both of these phenomena are more common in municipalities that have experienced a close PAN victory. Deadly conflicts between police and drug traffickers are relatively rare, occurring in only 20 municipality-months and 12 municipalities with a vote spread of five percentage points or less. Following close elections, these confrontations are fifty percent more likely to occur in municipalities where the PAN barely won than in municipalities where they barely lost. As regards arrests, the confidential federal government database of drug-related arrests unfortunately includes only high level arrests, since most other drug-related arrests are never prosecuted. High level arrests occurred 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 only 26 in municipalities where they barely lost. Given the rarity of these events, there is not much power for conducting a rigorous econometric analysis. When I do analyze these outcomes using the RD approach, the coefficients on PAN win are positive and marginally significant in some specifications (results available upon request).

Table 2 provides robust evidence that close PAN victories increase drug trade-related violence. Next, I briefly explore whether there are heterogeneous effects based on local political characteristics. The dependent variable in all columns of Table 3 is the average probability that a drug trade-related homicide occurs in a given month during the post-inauguration period, and the coefficients are estimated using local linear regression.[24] For comparison purposes, column (1) of Table 3 reports the baseline result from column (1) of Table 2. Next, column (2) examines a specification that distinguishes between municipalities where the PAN was the incumbent and municipalities where another party held the incumbency.[25] This specification includes the same terms as the baseline RD specification in equation (2) and also interacts PAN win, spread, and PAN win $\times$ spread with the PAN incumbency dummy. The estimated effect on violence of a PAN mayor taking office, relative to a non-PAN mayor taking office, is large and statistically significant regardless of whether the PAN held the incumbency. Prior to the close elections, the average probability of a drug trade-related homicide in a given municipality-month is modestly higher in municipalities with a PAN incumbent than it is in municipalities with a mayor from a different party (0.067 as compared to 0.048). Following the inauguration of closely elected PAN authorities, violence increases sharply regardless of the party of the incumbent. In contrast, following

[24] As documented Table A2 in the online appendix, the results are very similar when I instead use a panel data specification.

[25] In Mexico, mayors cannot run for re-election, so regardless of the party of the incumbent a new politician always takes office with each electoral cycle.

the inauguration of closely elected non-PAN authorities, violence decreases slightly and by a similar amount regardless of the party of the incumbent. These findings are consistent with descriptive evidence on Mexican violence outbreaks since 2006. This evidence shows that once violence increases, it may increase further but typically does not decline to pre-outbreak levels (Guerrero, 2011). The findings also suggest that PAN mayors narrowly elected in 2007 and 2008 may have been tougher on drug trafficking than their PAN predecessors, who were elected before drug trafficking became a major policy issue.

Column (3) reports a specification that distinguishes between whether the PAN candidate faced an opponent from the historically dominant PRI party, which opposed the PAN in around three quarters of elections. There are not statistically significant differences in drug trade-related violence in municipalities where the PAN mayor faced a PRI opponent as compared to municipalities where the PAN mayor faced an opponent from another party.

Next, columns (4) and(5) present further evidence that the effects documented in Table 2 result specifically from the PAN taking office. Recall that the sample for the results presented thus far includes municipalities with close elections where a PAN candidate was the winner or runner-up. In contrast, column (4) examines close elections where the PRI and PRD - Mexico's two other major parties - received the two highest vote shares. The PAN win dummy in the RD specification is replaced by a PRI win dummy. While the coefficient on PRI win is positive, it is about half the magnitude of the coefficient on PAN win in the baseline specification and is not statistically significant. Column (5) includes all close elections in the sample, regardless of which parties received the two highest vote shares. The PAN win dummy is replaced by a dummy equal to one if there was an alternation in the political party of the mayor. As expected given the results in columns (2) and (4), the coefficient on the alternation indicator is small and statistically insignificant.

Finally, column (6) examines all municipalities where a PAN candidate was the winner or runner-up, reporting results from an ordinary least squares regression of the probability that a drug trade-related homicide occurs in a given month during the post-inauguration period on the PAN win dummy, controls, and state fixed effects. While the coefficient on PAN win is positive, it is small in comparison to the estimate from the RD, with a magnitude of 0.01, and it is not statistically significant. Politics are likely to be meaningfully different in municipalities with very competitive elections as compared to municipalities with uncompetitive elections, and omitted variables bias in the ordinary least squares regression could also explain the difference between the estimates in column (1) versus column (6). Section 5 will use only the plausibly exogenous variation generated by close PAN elections to identify spillover effects. It will use all of these close elections, since the direct effects on violence are similar regardless of the party of the incumbent or the opponent.

4.4 Trafficking Industrial Organization and Violence

Regression discontinuity estimates show that drug trade-related violence in a municipality increases substantially after the close election of a PAN mayor. I now examine some potential mechanisms linking close PAN victories to large increases in violence. More than eighty-five percent of the drug trade-related homicides consist of people involved in the drug trade killing each other. The evidence presented in this section suggests that the violence reflects rival traffickers' attempts to wrest control of territories after crackdowns initiated by PAN mayors have challenged the incumbent criminals.

I begin by categorizing 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).[26] Municipalities with no known drug trade presence had not had any 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 purposes, column (1) of Table 4 reports the baseline local linear regression result from column (1) of Table 2 and column (2) reports the baseline differences-in-differences estimate from column (6) of Table 2. Next, column (3) uses a local linear regression specification to explore the relationship between the violence response to a close PAN victory and the structure of the drug trade. The dependent variable is the average probability that a drug trade-related homicide occurs in a given month during the post-inauguration period. The specification includes the same terms as the baseline RD specification in equation (2), as well as interacting PAN win, spread, and PAN win $\times$ spread with the dummies for the three categories of drug trade presence. No known drug trade presence is the omitted category.

The estimates show that the effect of close PAN victories on violence is extremely large in municipalities controlled by a major DTO that border a rival DTO's territory. A close PAN victory increases the probability that a drug trade-related homicide occurs in a given month by a highly significant 53 percentage points. The estimated effect of 14.6 percentage points for municipalities controlled by a major DTO that do not border territory controlled by a rival is considerably smaller but still statistically significant at the 5% level. The estimated effects of close PAN victories on violence in municipalities with a local drug gang or with no

[26]The major DTOs during the sample period are Beltran, Familia Michoacana, Golfo, Juarez, Sinaloa, Tijuana, and Zetas.

known drug trade presence are small and statistically insignificant.

To examine the robustness of this result, column 4 of Table 4 reports 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. The coefficient on post-inauguration $\times$ PAN win $\times$ borders rival, equal to 0.524, is nearly identical to the analogous coefficient on PAN win $\times$ borders rival in column (3) and is statistically significant at the one percent level. The violence effect for municipalities with a major DTO that do not border territory controlled by rival DTOs is also similar to the effect estimated by local linear regression. 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.[27] While these effects are larger than those estimated by local linear regression, both specifications estimate that the violence effects for these municipalities are smaller than the effects for municipalities with a major DTO. Columns (5) and (6) show that when a quadratic instead of a linear functional form is used for the RD polynomial, the results are qualitatively similar (although the still very large effect for municipalities bordering a rival is no longer statistically significant in column 5).[28]

Next, I use the shortest paths trafficking model to calculate the total detour costs that would be imposed if trafficking routes could no longer pass through a municipality. Total 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 the municipality. Columns (7) through (12) interact PAN win or PAN win $\times$ post with standardized total detour costs.[29] 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 in the local linear regression specification. This can be compared to the 8.7 percentage point effect of close PAN victories at the sample mean of detour costs. Similar patterns arise when the panel specification is used (column 8) and when higher order RD polynomials are used (columns 9 through 12). In summary, violence increases the most in municipalities that impose the greatest detour costs to circumvent, and hence are likely to be valuable to control.

[27] The fact that the estimates are similar for these groups of municipalities suggests that local drug gang presence may be under-reported.

[28] There is not enough variation in the data to precisely estimate a local regression with four separate cubic vote spread trends on either side of the discontinuity. When I estimate a specification with the three PAN win x territorial ownership dummies and a single cubic vote spread term on either side of the discontinuity, the results are similar to those presented in Table 4.

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

The characteristics examined in Table 4 are highly correlated, and moreover the presence of drug trafficking groups is likely to be an outcome of the network structure of drug trafficking. Thus, I cannot separately identify the impacts of territorial ownership from the impacts of the routes structure. Nevertheless, together the results strongly suggest that the industrial organization of drug trafficking exerts important effects on the violence response to close PAN victories. While crackdowns likely reduce rents from illicit activities in the short-to-medium run, by weakening the incumbent criminal group they also reduce the costs of taking control of a municipality. Controlling the municipality could offer substantial rents from trafficking and the variety of other criminal activities that DTOs control once the crackdown has subsided. Because crackdowns may divert drug traffic while in effect, I now turn to an investigation of spillover effects.

5 A Network Analysis of Spillover Effects

This section uses the network model of the drug trade and plausibly exogenous variation provided by the outcomes of close elections to identify the spillover effects of local crackdowns. Correlations between policy in one municipality and drug trade-related outcomes elsewhere could occur for several reasons, as highlighted more generally by Manski's formal treatment of spillover effects (1993). First, correlations could result from environmental factors unrelated to the local policies under consideration. Second, they could occur because traffickers choose to operate in given geographic arrangements for reasons unrelated to policy. Finally, local drug trafficking policies in one municipality could exert spillover effects, influencing outcomes elsewhere. The plausibly exogenous variation provided by close elections allows spillovers to be isolated from other correlations in outcomes across municipalities.

This section begins by examining whether the simple shortest paths network model is predictive of the diversion of drug traffic following close PAN victories. Then, I specify and estimate a richer version of the model that incorporates congestion costs. Finally, I test whether PAN crackdowns exert spillover effects on violence and economic outcomes. The section concludes by discussing possible extensions to the analysis.

5.1 Do close PAN victories divert drug traffic?

I begin by examining whether close PAN victories divert drug traffic to alternative routes predicted by the shortest paths trafficking model. The costs of trafficking drugs through a municipality are assumed to increase to infinity (or, in the robustness checks, by some other positive proportion) for the remainder of the sample period following the inauguration of

PAN mayors elected by a vote spread of five percentage points or less.[30] Because municipal elections happen at different times throughout the sample period, this generates month-to-month plausibly exogenous variation in the shortest routes from producing municipalities to U.S. points of entry. I examine the relationship between model predicted variation in routes and variation in actual illicit drug confiscations, the best available proxy for actual illicit drug traffic, using the following regression specification:

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

where $conf_{mst}$ is actual illicit drug confiscations of domestically produced drugs in municipality m in month t. Both an indicator measure and a continuous measure are explored. $Routes_{mst}$ is a measure of predicted drug trafficking routes, ψ_{st} are month x state fixed effects, and δ_m are municipality fixed effects. Because variation in routes may be correlated across space, the error term is clustered simultaneously by municipality and state-month (following the two-way clustering of Cameron, Gelbach, and Miller, 2011). The sample excludes municipalities with close elections, since the aim of the model is to predict spillovers from these elections.[31] This empirical approach is summarized in Figure 1.

The confiscations data provide the value of all illicit drug confiscations made by Mexican authorities between December of 2006 and December of 2009 and were made available by confidential sources. The value of confiscations (evaluated at Mexican illicit drug prices) in a municipality-month must be equal to at least $1,000 USD to be included in the sample. Occasionally the total value of confiscations in a municipality-month is both less than $1,000 and positive, and such confiscations are very likely to be from individual consumers and not from drug traffickers.[32] The confiscations rate per unit of drug traffic likely differs depending on the political environment. However, because municipal elections only occur once every three years, local authorities typically do not change and the municipality fixed effects will absorb time invariant differences in the probability of confiscations across municipalities.

Panel A of Table 5 reports estimates from equation (5), using an indicator variable equal to one if a municipality has a predicted trafficking route in a given month as the routes measure. In column (1), the dependent variable is a dummy equal to one if domestically produced illicit drugs are confiscated in a given municipality-month. When a municipality

[30] 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.

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

[32] Estimates are robust to using a variety of different cut-offs for the minimum value of drugs confiscated to construct the confiscations dummy variable (results available upon request).

acquires a predicted trafficking route, drug confiscations increase by around 1.6 percentage points, relative to a sample average probability of confiscations in a given municipality-month of 5.3 percent. This correlation is statistically significant at the 1% level. In column (2), the dependent variable is equal to the log of the value (in US dollars) of domestic illicit drug confiscations in the municipality-month if confiscations are positive and equal to zero otherwise. Because all positive confiscation values are at least equal to 1,000 USD, this measure is always positive.[33] The correlation between the log value of confiscations and predicted trafficking routes is large, positive, and statistically significant at the one percent level. Acquiring a predicted trafficking route is associated with an increase in the value of confiscated drugs of around 18.5 percent. In Table A3 of the online appendix, I repeat the analysis in Table 5 using the number of predicted routes instead of the indicator routes measure and find similar results. The value of confiscations increases by 2.3 percent for each additional trafficking route acquired, and this effect is statistically significant at the one percent level.

One concern in interpreting these results is that the relationship between predicted trafficking routes and actual confiscations could result from the direct effects of PAN crackdowns. For example, if alternative shortest paths traverse nearby municipalities and if PAN authorities tend to coordinate with the military and federal police, who in turn become active in an entire region, this could lead to a correlation between changes in shortest routes and changes in confiscations in nearby municipalities. It is much more difficult to tell a story in which close PAN victories directly affect drug trade outcomes in municipalities located further away. Thus, columns (3) and (4) examine whether the model remains predictive when municipalities bordering those that have experienced a close PAN victory are dropped from the sample. The estimated coefficients are similar in magnitude to those reported in columns (1) and (2) and are statistically significant at the 5 percent level.

To shed further light on the plausibility of the model, columns (5) through (8) report placebo checks. First I assume, contrary to the regression discontinuity evidence, that the costs of passing through municipalities that have experienced a close PAN *loss* are infinity, whereas there is no additional cost beyond traversing the physical distance to traffic drugs through a municipality that has experienced a close PAN win. This provides a basic test of whether the model loses its predictive power when it uses the wrong shocks. Columns (5) and (6) show that the model does lose its predictive power when this implausible assumption is made.

[33]Working in logs is attractive because drug confiscations are highly right-skewed, with several major drug busts resulting in tens of millions of dollars worth of confiscated drugs. Using log values makes the data more normally distributed and aids in the interpretation of the results.

Next, columns (7) and (8) test whether variation in routes induced by close PAN victories is correlated with variation in cocaine confiscations. Because the network model only uses origins for domestically produced drugs, the predicted routes measure should be uncorrelated with confiscations of cocaine as long as cocaine routes have different origins. Columns (7) and (8) document that the coefficients on the predicted routes dummy are small and statistically insignificant, whether a dummy or value measure of cocaine confiscations is used as the dependent variable. These results lend further support to the validity of the model.

Thus far, I have assumed that the cost of passing through a municipality that has experienced a close PAN victory is infinity. Figure 5 explores whether the relationship between predicted trafficking routes and the value of domestic drug confiscations is robust to assuming that a close PAN victory proportionally increases the effective length of the edges in a municipality by a given factor α.[34] The x-axis plots values of α ranging from 0.25 to 10 and the y-axis plots the coefficient on the routes dummy when a close PAN victory is assumed to proportionately increase the effective length of edges in a municipality by α. 95% confidence bands are shown with a thin black line and 90% confidence bands with a slightly thicker black line.

Moving from left to right across the x-axis, the first two cost factors, 0.25 and 0.5, serve as placebo checks. The RD evidence indicates that a close PAN victory makes trafficking drugs more costly, whereas $\alpha = 0.25$ and $\alpha = 0.5$ imply that PAN victories reduce trafficking costs. These placebo estimates are small, and none are statistically significant at the 10% level. In contrast, the estimates for cost values greater than one are similar to the baseline estimate in Table 5 and all are statistically significant at the 5% level.[35]

5.2 A richer trafficking model

While the shortest paths model robustly and accurately predicts the diversion of drug traffic following PAN crackdowns, assuming that traffickers take shortest distance route is clearly a simplification. Before examining whether the diversion of drug traffic is accompanied by violence and economic spillover effects, I develop a richer version of the trafficking model that incorporates congestion costs. These costs introduce strategic interactions between traffickers, producing a potentially more nuanced framework for locating spillovers and conducting policy analysis. Because congestion costs are unknown, I specify a congestion cost function and estimate its parameters using the simulated method of moments and cross-

[34]For example, if the length of a road through a municipality equals 10 kilometers and $\alpha = 2$, before a close PAN victory it would cost 10 to traffic drugs through the municipality and afterwards it would cost 20.

[35]Cost values between 0.5 and 1.5 are not informative, as values close to 1 do not generate enough variation in the edge costs over time to create within-municipality variation in trafficking routes.

sectional data on confiscations from the beginning of the sample period. Every choice of the model's congestion parameters generates a set of moments that summarize model-predicted routes. I estimate the congestion parameters by matching these moments to their counterparts generated from data on actual illicit drug confiscations at the beginning of the sample period.

Recall from Section 3 that each origin i 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. Each of the destinations has a given size, approximated by the number of commercial lanes for terrestrial border crossings and the container capacity for ports. All destinations pay the same international price for a unit of smuggled drugs.

Let $\mathcal{P}_i$ denote the set of all possible paths between producing municipality i and the United States, let $\mathcal{P} = \cup_i \mathcal{P}_i$ denote the set of all paths between all producing municipalities and the United States, and let x_p denote the flow on path $p \in P$. Each edge $e \in E$ has a cost function $c_e(l_e, x_e)$, where l_e is the length of the edge in kilometers and $x_e = \sum_{p \in \mathcal{P} | e \in p} x_p$ is the total flow on edge e, which equals the sum of flows across the paths that traverse it. I do not impose costs for trafficking drugs through territory controlled by traffickers in a rival trafficking organization because 51% of producing municipalities are controlled by local gangs, and there is not information on which larger organizations, if any, these groups coordinate with to transport drugs to the United States. This simplification is discussed in more detail at the end of this section.

Each trafficker's objective is to minimize the costs of transporting drugs to U.S. points of entry, taking aggregate flows as given. Since the amount of drugs transported by a single agent is small relative to the total supply of drugs, this assumption appears reasonable and simplifies the analysis considerably. In equilibrium, the costs of all routes actually used to transport drugs from a given producing municipality to the U.S. are equal and less than those that would be experienced by reallocating traffic to an unused route. Formally, an equilibrium must satisfy the following conditions, first published by transportation analyst John Wardrop in 1952:

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 $x_p > 0\ x_{p'} = 0$, $\sum_{e \in p'} c_e(x_e, l_e) \geq \sum_{e \in p} c_e(x_e, l_e)$.

The equilibrium routing pattern satisfying these conditions is the Nash equilibrium of the game. Beckmann, McGuire, and Winsten (1956) proved that the equilibrium can be characterized by a straightforward optimization problem.[36] An equilibrium always exists,

[36] Specifically, the routing pattern x^{WE} is an equilibrium if and only if it is a solution to:

and if each c_e is strictly increasing, then the equilibrium is unique. Traffickers ignore the externalities that their use of a route imposes via congestion costs, and thus the equilibrium routing pattern will typically not be socially optimal.

While this game does not have a closed-form solution, for a given network, set of supplies, and specification of the congestion costs $c_e(\cdot)$ it can be solved using numerical methods. I use the Frank-Wolfe algorithm (1956), which generalizes Dantzig's well-known simplex algorithm to non-linear programming problems. Details are provided in the online estimation appendix, which describes the paper's estimation procedures.

Because the congestion costs are unknown, solving the problem requires specifying a function for the edge costs $c_e(l_e, x_e)$ and estimating its unknown parameters. I assume that the congestion costs on each edge take a Cobb-Douglas form, and explore the robustness of the model's predictions to several different specifications of these costs. In the most parsimonious version, border crossings impose a congestion cost 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 congestion parameters, $lanes$ is the number of commercial lanes, and $containers$ is the container capacity. δ captures the fact that as illicit traffic through a given crossing increases, the quality of hiding places may decline, the authorities may direct more or less attention towards the crossing per unit of traffic, and traffickers may engage in turf wars with each other. Congestion values are converted to the same units as physical distance costs by the parameters $\{\phi_t, \phi_p\}$. One might be concerned that this functional form is overly restrictive. While there is not enough variation in the data to estimate a separate congestion parameter for each of the 26 points of entry into the U.S., I do estimate a version of the model with six ϕ parameters: one for terrestrial points of entry in the bottom quartile of the size distribution (i.e. crossings with a single lane), three more for terrestrial points of entry in the other three quartiles (2 lanes, 3 to 9 lanes, and 10 to 17 lanes, respectively), one for ports with below median container capacity, and one for ports with above median container capacity.[37] This allows the model

$$\min \sum_{e \in E} \int_0^{x_e} c_e(z)dz \tag{6}$$

$$s.t. \quad \sum_{p \in \mathcal{P} | e \in p} x_p = x_e \quad \forall e \in E \tag{7}$$

$$\sum_{p \in \mathcal{P}_i} x_p = 1 \quad \forall i = 1, 2, \ldots, \quad \forall p \in \mathcal{P} \tag{8}$$

$$x_p \geq 0 \quad \forall p \in \mathcal{P} \tag{9}$$

[37]Median container capacity is 160,000 TEUs, which is divided by 10,000 to be in units comparable to the size of the terrestrial crossings. TEU stands for "twenty-foot equivalent units."

to more flexibly capture the relationship between congestion costs and the size of the U.S. points of entry. In the final version of the model, I estimate the seven congestion cost parameters for U.S. points of entry, as well as parameters for congestion costs on the interior edges. The congestion costs on the interior edges take the form: $dist_e \phi_{int} flow_e^{\gamma}$, where $dist_e$ is the length of the edge, and ϕ_{int} and γ are congestion parameters whose interpretation is analogous to the ϕ and δ parameters on U.S. points of entry.[38]

The congestion parameters are estimated using the simulated method of moments (SMM) and cross-sectional data on the value of illicit drug confiscations during the beginning of the sample period, which lasts from December of 2006, when the confiscations data become available, until the first authorities elected during the sample period take office in July of 2007. Every choice of the model's congestion parameters generates a set of moments that summarize the patterns of model-predicted routes, and I estimate the congestion parameters by matching these moments to their counterparts generated from data on the value of actual illicit drug confiscations. Formally, let $\{x_m\}$ denote the flows predicted by the trafficking equilibrium problem, aggregated to the municipal level, and let $\theta_0 \in \mathbb{R}^P$ denote the vector of congestion parameters plus one scaling parameter κ that maps predicted flows to predicted confiscations: $\hat{conf}_m = \kappa x_m, \kappa \in (0, \infty)$.[39] Let $g(X_m, \theta_0) \in \mathbb{R}^L$ denote a vector of moment functions that specifies the difference between observed confiscations and those predicted by the model, given the congestion costs described by θ_0. The number of moment conditions must be greater than or equal to the number of parameters for the model to be identified. The SMM estimator $\hat{\theta}$ minimizes a weighted quadratic form:

$$\theta = \underset{\theta \in \Theta}{\operatorname{argmin}} \frac{1}{M} \left[\sum_{m=1}^{M} \hat{g}(X_m, \theta) \right]' \Sigma \left[\sum_{m=1}^{M} \hat{g}(X_m, \theta) \right] \tag{10}$$

where $\hat{g}(\cdot)$ is an estimate of the true moment function, M is the number of municipalities in the sample, and Σ is an L x L positive semi-definite weighting matrix. If $\hat{\Lambda}$ is a consistent estimator of $\text{Var}[g(X_m, \theta_0)]$ and $\Sigma = \hat{\Lambda}^{-1}$, then the SMM estimator will be asymptotically efficient. The optimal SMM estimator can be obtained by first minimizing (10) using $\Sigma = I_L$, the identity matrix. From this first step, $\hat{\Lambda}$ can be calculated, and (10) can be re-optimized in a second step using $\Sigma = \hat{\Lambda}^{-1}$. Further details about the asymptotic properties of the

[38] When I instead specify the congestion costs on interior edges as $\phi_{int} flow_e^{\gamma}$ (i.e. congestion costs to traverse an edge are the same regardless of the length of the edge), the estimated routes and spillover patterns are broadly similar (results available upon request).

[39] κ likely varies with the local environment, but it is not possible to estimate this dependence. To the extent that the model is robustly predictive of the evolution of drug trade-related outcomes within municipalities over time, this suggests that the estimated parameters are reasonable despite the fact that confiscations are an imperfect proxy of actual illicit drug flows.

SMM estimator can be found in Pakes and Pollard (1989) and McFadden (1989).

Predicted confiscations on a given edge are not independent of predicted confiscations elsewhere in the network, introducing spatial dependence. Following Conley (1999), I replace the asymptotic covariance matrix Λ with a weighted average of spatial autocovariance terms with zero weights for observations further than a certain distance. I allow for correlation between municipalities located within 250 km of each other. More details are provided in the online estimation appendix.

Depending on the specification, there are four to ten parameters in θ. The moments match the mean model predicted and observed confiscations at ports, at terrestrial bordering crossings, and on interior links. They also match the interactions between port confiscations and the port's container capacity, between terrestrial crossing confiscations and the crossing's number of commercial lanes, between interior confiscations and the length of the interior edge, and between interior confiscations and the length of the detour required to circumvent the edge. For models that estimate six separate crossing congestion parameters, the moment conditions match predicted confiscations within a 100 kilometer radius of each U.S. point of entry to actual confiscations within a 100 kilometer radius. The estimates for the model with three congestion parameters are similar when these moments are included in the estimation, but I omit them in the baseline estimation because they are not necessary for identification and adding more moment conditions raises the risk of finite sample bias and related problems similar to those that arise with weak instruments in linear models (see Stock, Wright, and Yogo, 2002). Finally, the moment conditions match the model predicted and observed variance of confiscations across U.S. points of entry and across interior edges.

As is often the case with choice problems, the SMM objective function is not globally convex and hence minimizing it is non-trivial. Standard gradient methods may perform poorly, and thus I instead use simulated annealing, which is more suited to problems that lack a globally convex objective (Kirkpatrick, Gelatt, and Vecchi, 1983). Details about the estimation procedure are given in the online appendix.

Table 6 reports the simulated method of moments estimates of the cost function parameters. Conley standard errors are in brackets and robust standard errors are in parentheses. Column 1 reports estimates for the specification with parsimonious congestion costs on U.S. points of entry, column 2 reports estimates for the specification with more flexible congestion costs on U.S. points of entry, and column 3 reports estimates for the specification with congestion costs on both U.S. points of entry and interior edges of the road network.

All parameters are precisely estimated. δ, which captures the shape of the congestion costs on U.S. points of entry, ranges from 1.57 to 1.88, depending on the model specification. This implies that the costs of congestion increase as illicit drug traffic through points of entry to the U.S. rises. This is an intuitive finding given that hiding places may become worse and authorities may direct more attention towards a given point of entry as illicit flows through that point of entry increase. When the congestion costs on points of entry are allowed to take a more flexible form in column 2, the $\phi_t^{Q_i}$'s tend to increase somewhat with the size of the border crossing. In other words, the model estimates higher congestion costs on a ten lane border crossing edge with ten units of traffic than on a one lane edge with one unit of traffic. The model in column 3, which includes congestion costs on interior edges, estimates $\gamma = 0.11$. This implies that congestion costs on interior edges are concave. In equilibrium, the total costs imposed by congestion on U.S. points of entry in this specification are about 39 times larger than the total costs imposed by congestion on interior edges, suggesting that congestion at U.S. points of entry is more important than congestion within Mexico. This is not surprising, given the greater law enforcement presence at U.S. points of entry and the bottlenecks that they impose. All three models estimate that total congestion costs are nearly as large as total distance costs. Predicted routes for the pre-period, estimated using the parameters in column 1 of Table 6, are show in Figure 2. The routing patterns predicted by the other congestion cost specifications are reasonably similar.

The model parameters are estimated to match the cross-section of pre-period confiscation values, and the model is highly predictive of these confiscations. In a linear regression of actual municipal-level confiscations on model predicted confiscations, all three specifications have a t-statistic of between 7 and 8. The squared correlation coefficient is between 0.02 and 0.03. As would be expected, as more parameters are added to the model, the correlation coefficient increases somewhat. The model is also highly predictive of the intensive margin of confiscations. When comparing the actual confiscations indicator variable to the predicted confiscations indicator variable, the Pearson chi-squared statistic has a value of 100 for the 4 parameter model, 116 for the 8 parameter model, and 76 for the 10 parameter model, all of which have p-values near zero.

I now turn to an examination of whether the trafficking model, fitted on data from the beginning of the sample period, predicts the diversion of trafficking routes in response to close PAN victories occurring later in the sample period. I use the same empirical approach as I did for the shortest paths trafficking model, with the predicted routes measure in equation (5) calculated using the model with congestion. Due to space constraints, in the main text I report results for the routes measure calculated using the parameters in Column 1 of Table 6, because variation in these routes is the most highly correlated with variation in actual illicit drug confiscations. Tables A4, A5, and A6 in the online appendix repeats all analyses from the main text using the parameters in columns (2) and (3) of Table 6, documenting that the estimated spillovers in drug traffic, violence, and economic outcomes are broadly similar regardless of the congestion parameters used to predict trafficking routes.

Panel B of Table 5 examines the relationship between actual illicit drug confiscations and predicted routes from the model with congestion. As in the analysis with the shortest distance routes, I focus on the extensive margin of trafficking. In column (1), the dependent variable is a dummy equal to one if domestically produced illicit drugs are confiscated in a given municipality-month and equal to zero otherwise. When a municipality acquires a predicted trafficking route, drug confiscations increase by around 1.5 percentage points, and this correlation is statistically significant at the 1% level. In column (2), the dependent variable is equal to the log of the value (in US dollars) of domestic illicit drug confiscations in the municipality-month if confiscations are positive and equal to zero otherwise. Acquiring a predicted trafficking route is associated with an increase in the value of confiscated drugs of around 19.5 percent. Columns (3) and (4) document that these results are robust to excluding municipalities that border a municipality that has experienced a close PAN victory. Columns (5) and (6) show that the model loses its predictive power when the wrong shocks are used (that is, when I assume that PAN losses instead of PAN victories increase trafficking costs). Next, columns (7) and (8) document that the correlations between predicted domestic trafficking routes and the presence or value of cocaine confiscations are small and statistically insignificant. Finally, Figure 5 shows that the results are robust to varying the costs imposed by a close PAN victory. When close PAN victories are implausibly assumed to reduce the costs of trafficking drugs through a municipality, the model loses its predictive power. As shown in Table A4 in the online appendix, the above results are robust to using the other specifications of the congestion costs reported in Table 6. In the online appendix, I also repeat the analysis in Table 5 using the number of predicted routes instead of the indicator routes measure. While the value of confiscations increases for each additional trafficking route acquired, the relationship is not statistically significant at conventional levels.

Overall, while congestion does change the predicted routes somewhat, the model with congestion costs offers at best modest improvements in predictive power over the shortest paths model, which is already quite predictive of variation in illicit drug confiscations within municipalities over time. 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. I now turn to an examination of whether PAN crackdowns exert violence and economic spillovers.

5.3 Violence and economic spillovers

The results in Table 5 indicate that the trafficking model accurately predicts the diversion of illicit drug traffic following close PAN victories. Now, I use the predictions about the diversion of drug traffic to locate violence and economic spillover effects. Ideally, I would use predicted trafficking routes as an instrument for actual trafficking routes, but actual trafficking routes are unobserved. Thus, I focus on testing whether there is a reduced form relationship between predicted drug trafficking presence and violence or economic outcomes.

First I explore violence spillovers. Table 7 reports estimates from equation (5), with various violence measures used as the dependent variable. Panel A uses the shortest paths measure, and Panel B uses the routes measure from the model with congestion. Panel A of column (1) shows that the presence of a predicted trafficking route increases the probability that a drug trade-related homicide occurs in a given month by 1.3 percentage points (s.e.=0.5). This can be compared to the average sample probability of a drug trade-related homicide, which is equal to 4.4 percent. The estimated effect of 1.5 percentage points in Panel B is very similar. The effect estimated in Panel B increases slightly, to 1.8 percentage points, and remains statistically significant, when municipalities bordering a municipality that has experienced a close PAN victory are excluded from the sample, whereas the effect in Panel A becomes smaller and statistically insignificant. This suggests that the model with congestion costs may be better at predicting violence spillovers that are not in adjacent municipalities.

Congestion costs, both on interior edges and at U.S. points of entry, may partially reflect a higher probability of violent clashes when traffickers' routes coincide. I examine whether there is evidence for this in column (2), by regressing the drug trade-related homicide dummy on an indicator equal to one if a municipality contains one trafficking route in the relevant period and a separate indicator equal to one if it contains more than one trafficking route. No trafficking routes is the omitted category. The coefficients reported in Panel B, which are estimated using the model with congestion, provide suggestive evidence that traffickers are more likely to engage in violent conflicts when their routes coincide. The coefficient on the more than one route dummy is equal to 0.019 (s.e.= 0.007), whereas the coefficient on the single route dummy is equal to 0.008 (s.e.= 0.006). However, when the shortest path routes are used, the spillover effects on violence are estimated to be similar regardless of whether there is one or multiple routes in a municipality, indicating that the evidence in Panel B should be interpreted cautiously.

In columns (3) and (4), I report analogous specifications using monthly drug trade-related homicides per 10,000 municipal inhabitants as the dependent variable. The pattern of results is qualitatively similar to that in columns (1) and (2). However, the correlation between the routes dummy predicted using the model with congestion and the homicide rate, while positive and large relative to the sample mean, is not statistically significant.

Column (7) documents that the presence of a predicted trafficking route has no effect on the non-drug trade-related homicide rate. Finally, columns (8) and (9) report results from the placebo check in which close PAN losses rather than close PAN victories increase the costs of trafficking drugs. As expected, there is no longer a relationship between predicted routes and the drug trade-related homicide probability or rate.

Next, I turn to economic spillovers. I use quarterly data from the National Survey of Occupation and Employment (*Encuesta Nacional de Ocupación y Empleo*), collected by the National Institute of Statistics and Geography (INEGI), to construct measures of labor market outcomes for 2007 through 2009. These data are available for a sample of municipalities.[40] Table 8 reports the results from regressing male and female labor force participation and formal and informal sector wages of prime age males on the predicted trafficking routes dummy, state x quarter fixed effects, and municipality fixed effects.[41] Panel A predicts routes using the shortest paths model, and Panel B uses the model with congestion costs.

Overall, the economic spillover effects tend to be imprecisely estimated and thus should be interpreted cautiously. Nevertheless, they provide suggestive evidence - consistent with the qualitative evidence discussed in Section 2 - that drug trafficking organizations engage in widespread extortion, particularly of poorer citizens. The correlations between the routes dummy and male labor force participation (column 1) and formal sector wages (column 3) are statistically insignificant and tend to be relatively small. In contrast, columns (2) and (4) of Panel B document that the presence of a predicted trafficking route lowers informal sector wages by around 2.3 percent (s.e.= 1.3) and lowers female labor force participation by 1.26 percentage points (s.e.= 0.57), relative to an average female participation rate of 51 percent. The coefficients on the routes dummy in Panel A, which uses the shortest paths model, are also large but are noisily estimated. Columns (5) and (6) show that the estimates in both panels are similar when municipalities bordering a municipality that has experienced a close PAN victory are excluded from the sample. Finally, columns (7) and (8) use the placebo model in which close PAN losses increase the costs of trafficking drugs through a municipality. The correlations between the routes dummy and both female labor force participation and informal sector wages, while imprecisely estimated, are smaller than the correlations shown in columns (2) and (4) and are statistically insignificant. While the economic data do not

[40] I have also examined the direct effects of close PAN victories on economic outcomes. Because the economic data are from a sample, municipalities near the PAN win-loss threshold with economic data are limited in number, and the direct economic effects (available upon request) are imprecisely estimated.

[41] The analysis of wages is limited to prime age males because they tend to participate inelastically in the labor force, reducing concerns about selection bias in the wage regressions.

provide as much power as the confiscations and violence data, overall the evidence suggests that drug trafficking presence exerts economic effects on the general population.

5.4 Possible Extensions

Both versions of the trafficking model predict the diversion of drug traffic following close PAN victories. With access to additional data, it would be straightforward to further enrich the analysis. For example, I do not examine cocaine trafficking because of the absence of reliable data on cocaine points of entry into Mexico. Once cocaine enters Mexico, however, terrestrial trafficking is similar to that of other domestically produced drugs. Thus, with reliable data on cocaine points of entry, a similar approach could be applied to this drug.

With better data, the trafficking model could also explicitly incorporate territorial ownership by drug trafficking organizations. 51 percent of producing municipalities were controlled by a local drug gang in the period examined in this study, and we do not know which trafficking organizations, if any, these gangs allied with to transport their drugs to the United States. Thus, I am unable to incorporate territorial ownership into the model. I do, however, explore the importance of territorial ownership by conducting the following exercise. I begin by limiting the sample to edges emanating from nodes that meet the following criteria: 1) the node is traversed in the equilibrium with congestion costs by a trafficking route whose origin is controlled by a major DTO, 2) the node forks into at least one edge which is controlled by a DTO that controls the origin of a route traversing that node, and 3) the node also forks into at least one edge that is not controlled by the above-mentioned DTO. This sample includes 633 edges (217 nodes), as compared to 17,453 edges (13,969 nodes) in the full network. I find that the trafficking model on average under-predicts flows on edges described by the second criterion and over-predicts flows on edges described by the third criterion. This suggests that territorial ownership is relevant. The network model does a reasonable job predicting drug traffic without incorporating territorial ownership, perhaps because territorial ownership has responded endogenously to network characteristics. If additional information were to become available, this result suggests that the model's predictions could be further improved by incorporating territorial ownership.

The network approach developed in this study could also be extended to other contexts in which combating drug trafficking is a policy priority. This includes areas such as Afghanistan, Myanmar, Thailand, Vietnam, Laos, certain provinces in China, Colombia, Peru, and Bolivia, which are major centers of heroin and cocaine production and trafficking. Given that these regions have a much sparser road network than Mexico, presumably a network analysis of terrestrial drug trafficking would be more straightforward.

6 Policy Implications

This study shows that government policy impacts drug trade-related violence and trafficking costs. Reducing the profits of organized criminal groups is an important objective of drug policy, as it reduces the resources that traffickers have to corrupt government officials and to threaten public security (Shirk, 2011). However, policies that increase trafficking costs may have the unintended consequence of increasing violence. This section uses the trafficking model and spillover patterns to examine how scarce law enforcement resources can be allocated to increase trafficking costs by as much as possible. It also discusses how the violence response to this policy may be reduced.

There are several reasons why explicitly considering the network structure of trafficking is useful for the efficient allocation of law enforcement resources. Most obviously, allocating a police checkpoint or other resources to a road with extensive drug traffic will not necessarily increase trafficking costs substantially, since there could be a cheap detour. Moreover, increasing the cost of traversing an edge could actually decrease total trafficking costs because of the externalities from congestion. This result, known as Braess's paradox after mathematician Dietrich Braess, has been documented in a number of real world traffic congestion examples.[42] It occurs for around fifteen percent of edges in the trafficking equilibrium predicted by this study's analysis. Finally, because of the network structure of trafficking, the effects of law enforcement in different locations will be interconnected. The network model, combined with a simple algorithm for the allocation of law enforcement resources, incorporates all three of these phenomena.

I specify the government's resource allocation problem as follows: the government's objective is to maximize the total costs that traffickers incur by allocating resources such as police checkpoints to k edges in the road network. This policy increases the cost of trafficking drugs on each of the selected edges, which are referred to as *vital edges*, by a pre-specified amount p_e. Traffickers respond by selecting the cheapest routes given the new set of edge costs, accounting for changes in congestion. The government faces a resource constraint and must pay a cost r_e to send a unit of law enforcement to each edge e.

With data about the types of law enforcement resources employed in PAN crackdowns, one could use the network model to estimate p_e, and r_e could be calculated from administrative data. However, these data cannot be released to researchers, and conducting a comprehensive analysis of the deployment of Mexican military and law enforcement resources is beyond the scope of this study in any case. Instead, I provide the following illustrative

[42]For examples of Braess's paradox in traffic congestion in Seoul, New York, Berlin, Boston, and London, see Youn, Gastner, and Jeong (2008); Easley and Kleinberg (2008, p. 71); and Knodel (1969, p. 57-59).

example of how the network approach can contribute to the design of effective law enforcement policies. Suppose that the government's budget allows it to allocate a pre-specified number of police checkpoints. I estimate a reasonable value for p_e, the amount that checkpoints increase the effective length of an edge, by using the impacts of close PAN victories as a benchmark. The network model best predicts the diversion of drug traffic following PAN crackdowns when I assume that they increase trafficking costs by a factor of three. Thus, I assume that each police checkpoint increases the effective length of selected edges by $3 \times 9 = 27$ kilometers, where 9 kilometers is the average edge length in the network.[43] With the appropriate data, it would be straightforward to construct estimates of c_e and r_e and extend the analysis to multiple types of resources (Israeli and Wood, 2002).

The government's resource allocation problem is a Stackelberg network game with a large number of Nash followers (Baş and Srikant, 2002; Stackelberg, 1952). In the first stage, the government allocates police checkpoints to k vital edges. In the second stage, traffickers respond by simultaneously selecting trafficking routes. The scenario in which traffickers respond to the government's action by choosing the shortest path to the U.S. is a special case in which congestion costs are zero. Ball, Golden, and Vohra (1989) showed that this special case is NP hard, and thus it follows that the more general problem is also NP-hard. That is, the time required to solve for the optimum increases quickly as the size of the problem grows. Even if we focused on the simpler model with no congestion costs, solving for the optimum using an exhaustive search would have an order of complexity of $O(V!)$, where V (the number of vertices) equals 13,969, and thus would take trillions of years to run. Intuitively, the problem is challenging because allocating police resources to two edges at the same time might increase the objective function more than the summation of changes in the objective function when resources are allocated to each edge separately, and hence the order in which a solution algorithm proceeds may matter.

Developing algorithms for problems similar to the one described here is an active area of operations research and computer science. For example, researchers have examined the problem of identifying vital edges in critical infrastructure networks, such as oil pipelines and electricity grids, so that these edges can be better defended against terrorist attacks and the systems made more robust (see, for example, Brown, Carlyle, Salmerón and Wood, 2005). To the best of my knowledge there are currently no known algorithms for solving the government's resource allocation problem that are both exact (guaranteed to converge to

[43] An alternative assumption is that police checkpoints multiply the effective length of edges by a given factor. However, this would imply that checkpoints increase the costs of longer edges by more than they increase the costs of shorter edges. The multiplicative costs assumption appears reasonable for PAN crackdowns, as larger municipalities have more police and are likely to receive larger federal police and military contingents, but the assumption appears less appropriate for police checkpoints.

optimality) and feasible given the size of the network, either for the network with congestion or for the simpler problem in which congestion costs are zero.[44] Developing a fast, exact algorithm for this problem is a challenging endeavor that is significantly beyond the scope of the current study. Thus, I instead use the following approximate heuristic to solve for the k vital edges:

1. For each of k iterations, calculate how total trafficking costs respond to individually increasing the edge lengths of each of the N most trafficked edges in the network.
2. Assign each element of this set of N edges a rank, $m = 1 \dots N$, such that the removal of edge $m = 1$ would increase trafficking costs the most, the removal of edge $m = 2$ would increase trafficking costs the second most ... and the removal of edge $m = N$ would increase trafficking costs the least.
3. Increase the effective length of the edge with $m = 1$ by a pre-specified amount.
4. Terminate if k iterations have been completed and return to step 1 otherwise.

While this algorithm does not guarantee convergence to the optimum, encouragingly it offers a solution that is robust to varying the details of the algorithm. Figure 6 plots the results of this exercise with $k = 25$ and $N = 250$, highlighting municipalities that contain a vital edge in red. The average monthly drug trade-related homicide rate between 2007 and 2009 is plotted in the background. Allocating police checkpoints to these 25 edges increases the total length of the network by 0.0043 percent and increases total trafficking costs by 17 percent. Results are similar when I instead: a) choose values of N ranging from 100 to 500, b) alternate in step 3 between selecting the edges with $m = 1$ and $m = 2$, c) alternate in step 3 between selecting the edges with $m = 1$, $m = 2$, and $m = 3$, and d) remove the edge with $m = 2$, $m = 3$, $m = 4$, or $m = 5$ when $k = 1$ and remove the edge with $m = 1$ when $k = 2 \dots 25$.

One concern with targeting law enforcement resources towards vital edges is that this may increase violence substantially. To the extent that the government aims to both increase trafficking costs and minimize the probability of a large violence response, vital edges can

[44] Malik, Mittal, and Gupta (1989) suggest an algorithm for finding k vital edges in the shortest path problem, but unfortunately it is theoretically flawed (see Israeli and Wood (2002) for a discussion). The most closely related work is by Israeli and Wood (2002), who develop an efficient algorithm for solving for k vital edges in the context of a shortest path problem on a directed graph with a single origin and destination. Even if the algorithm, which involves considerable mathematical machinery, could be extended to this paper's undirected graph with multiple origins, it is unlikely to be feasible on a network of the size examined here and does not accommodate congestion costs. Existing vital edge algorithms focus on shortest path or max flow problems (i.e. Lim and Smith, 2007) , and to the best of my knowledge researchers have not examined the vital edge problem in a congested network.

be distinguished based on a crackdown's predicted direct and spillover effects on violence. Moreover, if the government credibly signals a permanent law enforcement presence on vital edges, this might reduce the violence response since the returns to controlling those edges would be permanently reduced. Hence the expected returns to fighting over their control would be lower.

A potential alternative strategy that does not require a network analysis would be for the government to place checkpoints in municipalities with the most violence. These municipalities may contain a disproportionate number of vital edges if the control of vital edges is contested. Figure 6 shows that while some vital edges are in high violence municipalities, others are not, and thus the identification of vital edges offers a distinct contribution.

In summary, the network approach provides unique information with the potential to contribute to a coordinated law enforcement policy. It may (or may not) be that policies in consumer countries, such as the legalization of marijuana or more concerted efforts to reduce illicit drug consumption by individuals already under the supervision of the criminal justice system, would reduce profits of drug traffickers more than well-coordinated interdiction efforts in Mexico. Alternatively, some have called on Mexico to abandon interdiction altogether. However, legalization in the U.S. is unlikely to be politically feasible in the immediate future, and giving up on interdiction altogether is also improbable given the threats that traffickers pose through their varied criminal activities and influences on public institutions. Thus, there is likely to be a continued emphasis on how interdiction policies in Mexico can be improved. A frequent critique of the Mexican government's policy towards drug trafficking is that it has tended to indiscriminately target drug traffickers, rather than focusing resources on a more systematic and theoretically informed approach (Guerrero, 2011; Kleiman, 2011). By incorporating spillovers and well-defined predictions about traffickers' behavior, the network approach provides unique information with the potential to contribute to a more nuanced and efficient law enforcement policy.

7 Conclusion

This study examines how drug traffickers' economic objectives influence the direct and spillover effects of Mexican policy towards the drug trade. It 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 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. These results support the hypothesis that government policy has led to large increases in violence, primarily through spurring conflicts between rival traffickers. Second, the study accurately predicts the diversion of drug traffic following close PAN victories. It does this by estimating a model of equilibrium routes for trafficking drugs across the Mexican road network to U.S. points of entry. When drug traffic is diverted to other municipalities, violence in these municipalities increases. Moreover, female labor force participation declines and informal sector wages fall. These results corroborate qualitative evidence that traffickers extort informal sector producers. Finally, I show that the network approach can serve as a tool for the efficient allocation of law enforcement resources.

These results demonstrate how traffickers' economic objectives and constraints imposed by the routes network affect the policy outcomes of the Mexican Drug War. They 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. In addition to helping governments address the immediate challenges of reducing the profits and other operational objectives of organized criminals, a network-informed approach may aid in pursuing longer-term policy goals. In making the case for why combating drug trafficking is important for Mexico's long-term interests, President Felipe Calderón argued that organized criminals had infiltrated public institutions to such an extent that challenging these groups was necessary for protecting national security and preventing institutional deterioration. 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 public 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.

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Table 1: Pre-characteristics

	(1)	(2)	(3)	(4)	(5)
	5% vote spread PAN lost	PAN won	t-stat on means difference	RD estimate	t-stat on RD estimate
Crime characteristics					
Monthly drug-trade related homicides (Dec. '06 - Jun. '07)	0.113	0.176	(0.41)	0.07	(0.36)
Monthly drug-trade related homicide dummy (Dec. '06 - Jun. '07)	0.042	0.031	(-0.51)	-0.01	(-0.46)
Monthly police-criminal confrontation deaths (Dec. '06 - Jun. '07)	0.146	0.086	(-0.57)	-0.20	(-0.75)
Monthly confrontation deaths dummy (Dec. '06 - Jun. '07)	0.043	0.043	(-0.01)	-0.02	(-0.66)
Annual homicide rate per 100,000 inhab. (1990-2006)	15.01	13.68	(-0.46)	-0.19	(-0.63)
Municipal political characteristics					
Mun. taxes per capita (2005)	56.75	59.84	(0.22)	13.9	(0.73)
Mun. taxes per $ income (2005)	0.001	0.001	(0.05)	0.0001	(0.95)
PAN incumbent	0.366	0.371	(0.07)	-0.02	(-0.37)
PRD incumbent	0.037	0.057	(0.59)	0.01	(0.16)
% alternations (1976-2006)	0.418	0.400	(-0.34)	0.006	(0.30)
PRI never lost (1976-2006)	0.073	0.071	(-0.97)	-0.03	(-0.39)
Demographic characteristics					
Population (2005)	5099	6026	(0.35)	336	(0.84)
Population density (2005)	191.1	220.2	(0.41)	-118	(-0.80)
Migrants per capita (2005)	0.018	0.016	(-0.69)	-0.0007	(-0.35)
Economic characteristics					
Income per capita (2005)	4483	4285	(-0.53)	0.02	(0.03)
Mun. Gini (2005)	0.421	0.410	(-1.47)	-0.005	(-0.57)
Malnutrition (2005)	31.20	32.76	(0.52)	-0.37	(-0.01)
Mean years schooling (2005)	6.18	6.26	(0.32)	0.06	(0.21)
Infant mortality (2005)	22.26	22.54	(0.22)	0.28	(0.18)
HH w/o access to sewage (2005)	8.436	8.505	(0.05)	2.01	(0.71)
HH w/o access to water (2005)	18.22	16.14	(-0.62)	-0.81	(-0.20)
Marginality index (2005)	-0.119	-0.154	(-0.23)	-0.05	(-0.26)
Road network characteristics					
Average detour length (km)	157	220	(0.46)	23.6	(0.47)
Total roads (km)	66.4	111.5	(1.28)	54.1	(1.34)
Road density (km/km^2)	0.129	0.156	(1.23)	0.003	(0.11)
Distance U.S. (km)	732.3	700.8	(-0.62)	-9.91	(-0.10)
Geographic characteristics					
Elevation (m)	1380	1406	(0.19)	-45.3	(-0.31)
Slope (degrees)	3.25	3.62	(0.89)	0.07	(0.12)
Surface area (km^2)	739	1834	(1.34)	1249	(1.44)
Average min. temperature, C (1950-2000)	12.2	11.8	(-0.57)	-0.04	(-0.04)
Average max. temperature, C (1950-2000)	26.6	26.4	(-0.45)	-0.10	(-0.14)
Average precipitation, cm (1950-2000)	105	115	(0.82)	5.9	(0.46)
Observations	**82**	**70**			

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, using GIS software. 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. Column (3) reports the t-statistic on the difference in means between municipalities where the PAN barely won and where they barely lost. Column (4) reports the coefficient on PAN win from equation (2) when the respective characteristic is used as the dependent variable, and column (5) reports 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)
	Elections involving PAN			Alternative samples		
		PAN	PRI	PRI v.	Any	All
	Baseline	Incumbent	Opponent	PRD	alternation	muns.
PAN win	0.084***	0.067**	0.070**			0.012
	(0.027)	(0.028)	(0.029)			(0.010)
PAN win		0.055				
× PAN Incumbent		(0.040)				
PAN win			0.021			
× PRI opponent			(0.032)			
PRI win				0.049		
				(0.035)		
Alternate					0.013	
					(0.018)	
R-squared	0.648	0.648	0.648	0.571	0.554	0.670
Observations	430	430	430	259	780	614
PAN incumbent effect		0.122***				
		(0.040)				
PRI opponent effect			0.090***			
			(0.030)			

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. All columns are estimated using local regression, with separated 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)
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: Trafficking Model Parameter Estimates

	(1)	(2)	(3)
	Crossing Costs		Full
	parsimonious model	flexible model	congestion costs
ϕ_t	62.34***		
	[2.72]		
	(1.41)		
ϕ_p	36.48***		
	[2.07]		
	(1.40)		
ϕ_t^{Q1}		3.24***	13.00***
		[0.30]	[1.27]
		(0.25)	(1.19)
ϕ_t^{Q2}		13.19***	9.29***
		[2.14]	[0.34]
		(1.89)	(0.33)
ϕ_t^{Q3}		13.86***	21.26***
		[4.37]	[0.54]
		(4.08)	(0.52)
ϕ_t^{Q4}		18.81***	20.22***
		[0.86]	[0.62]
		(0.83)	(0.57)
ϕ_p^{small}		64.47***	70.990***
		[9.76]	[1.29]
		(9.16)	(1.28)
ϕ_p^{large}		55.34***	43.50**
		[8.43]	[21.73]
		(7.46)	(17.03)
ϕ_{int}			0.015***
			[0.004]
			(0.003)
δ	1.88***	1.57***	1.86***
	[0.05]	[0.15]	[0.17]
	(0.04)	(0.12)	(0.16)
γ			0.11**
			[0.06]
			(0.05)
κ	0.763***	0.91***	0.79***
	[0.07]	[0.08]	[0.07]
	(0.06)	(0.07)	(0.06)

Notes: Column 1 reports the simulated method of moments parameter estimates for the model with parsimonious congestion costs on U.S. points of entry, Column 2 reports the parameter estimates for the model with flexible congestion costs on U.S. points of entry, and Column 3 reports the parameter estimates for the model with congestion costs on both U.S. points of entry and interior edges. Conley (1999) standard errors are in brackets, and robust standard errors are in parentheses.

Table 7: Violence Spillovers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full Sample		Full Sample Drug-related homicide		Limited Sample		Full Sample Non-drug homicide	Placebo Paths 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

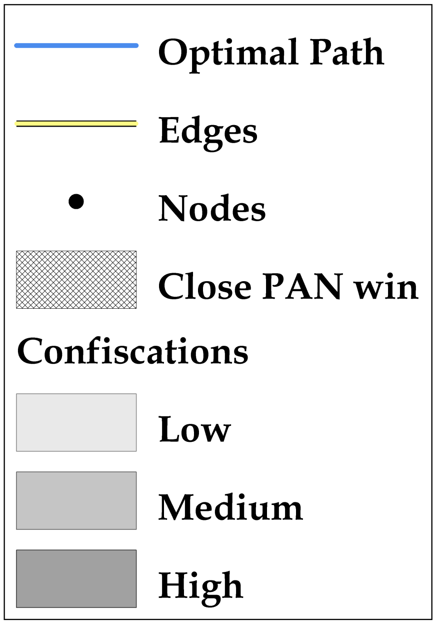
Notes: The dependent variable in columns (1), (2), (5) and (8) is a dummy equal to 1 if a drug trade-related homicide occurred in a given municipality-month; the dependent variable in columns (3), (4), (6), and (9) is the drug trade-related homicide rate per 10,000 municipal inhabitants, and the dependent 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%.

Table 8: Economic Spillovers

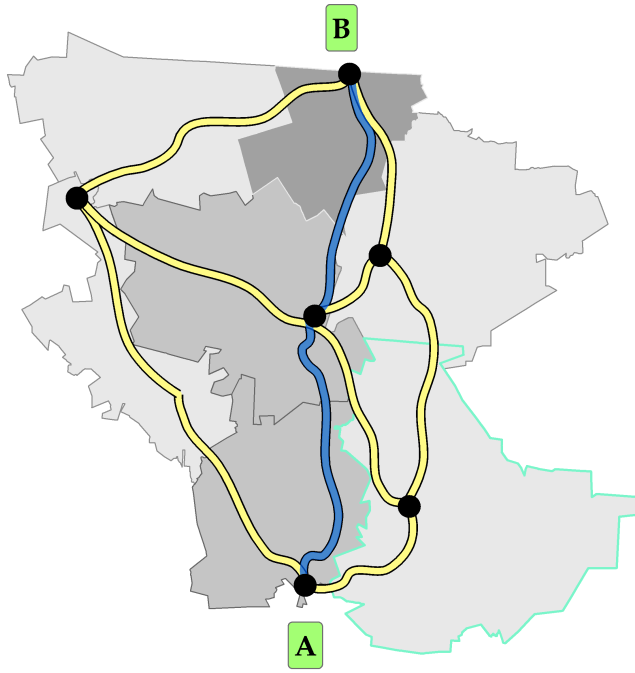
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full sample				Limited sample		Placebo Paths	
	Male participation	Female participation	Formal sector log wages	Informal sector log wages	Female participation	Informal wages	Female participation	Informal wages
Panel A: Shortest Paths								
Predicted routes dummy	-0.124	-0.756	0.020	-0.023	-0.784	-0.030	-0.691	0.022
	(0.513)	(1.038)	(0.022)	(0.020)	(1.622)	(0.027)	(1.040)	(0.023)
Panel B: Model with Congestion Costs								
Predicted routes dummy	-0.242	-1.261**	0.013	-0.022*	-1.558**	-0.028*	-0.520	-0.014
	(0.302)	(0.570)	(0.012)	(0.013)	(0.673)	(0.017)	(0.636)	(0.020)
State x quarter FE	yes	yes	yes	yes	yes	yes	yes	yes
Municipality FE	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.52	0.79	0.18	0.09	0.79	0.09	0.79	0.13
Municipalities	880	880	879	871	709	703	880	871
Observations	9,821	9,821	407,204	148,302	7,887	114,633	9,821	148,302
Mean Dep. Var.	89.58	51.46	3.34	3.24	44.81	3.03	51.46	3.24

Notes: The dependent variable in column (1) is average municipal male labor force participation; the dependent variable in columns (2), (5), and (7) is average municipal female labor force participation, the dependent variable in column (3) is log wages of formal sector workers; and the dependent variable in columns (4), (6), and (8) is log wages of informal sector workers. Columns (7) and (8) use the placebo network, as described in the text. All columns include quarter x state and municipality fixed effects. Column (1) weights by the square root of the municipality's male population and columns (2), (5), and (7) weight by the square root of the municipality's female population. The sample in columns (5) and (6) excludes municipalities that border a municipality that has experienced a close PAN victory. Standard errors clustered by municipality and quarter x state are reported in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%.

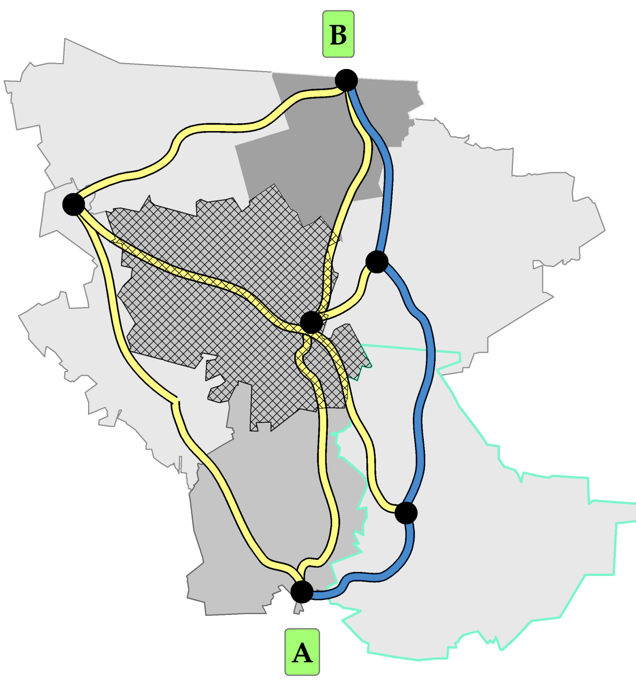
Figure 1: Illustration of Spillovers Methodology



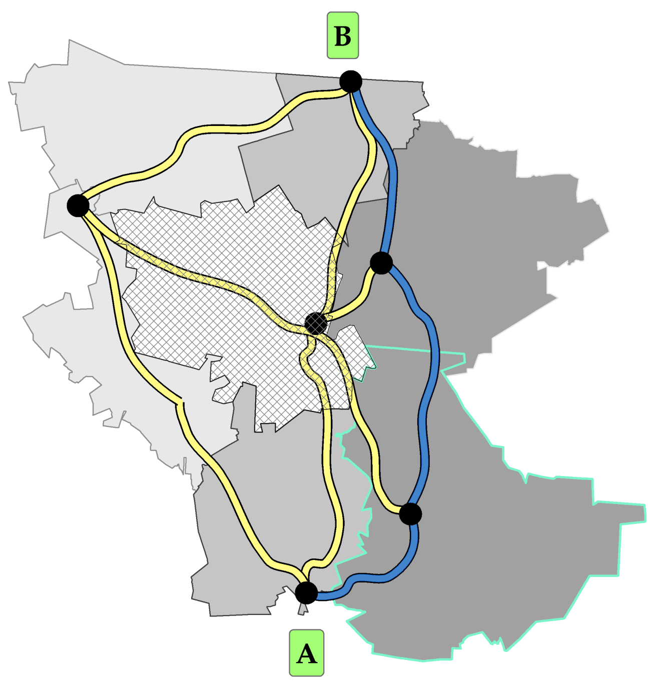
(a) Legend



(b) Basic environment

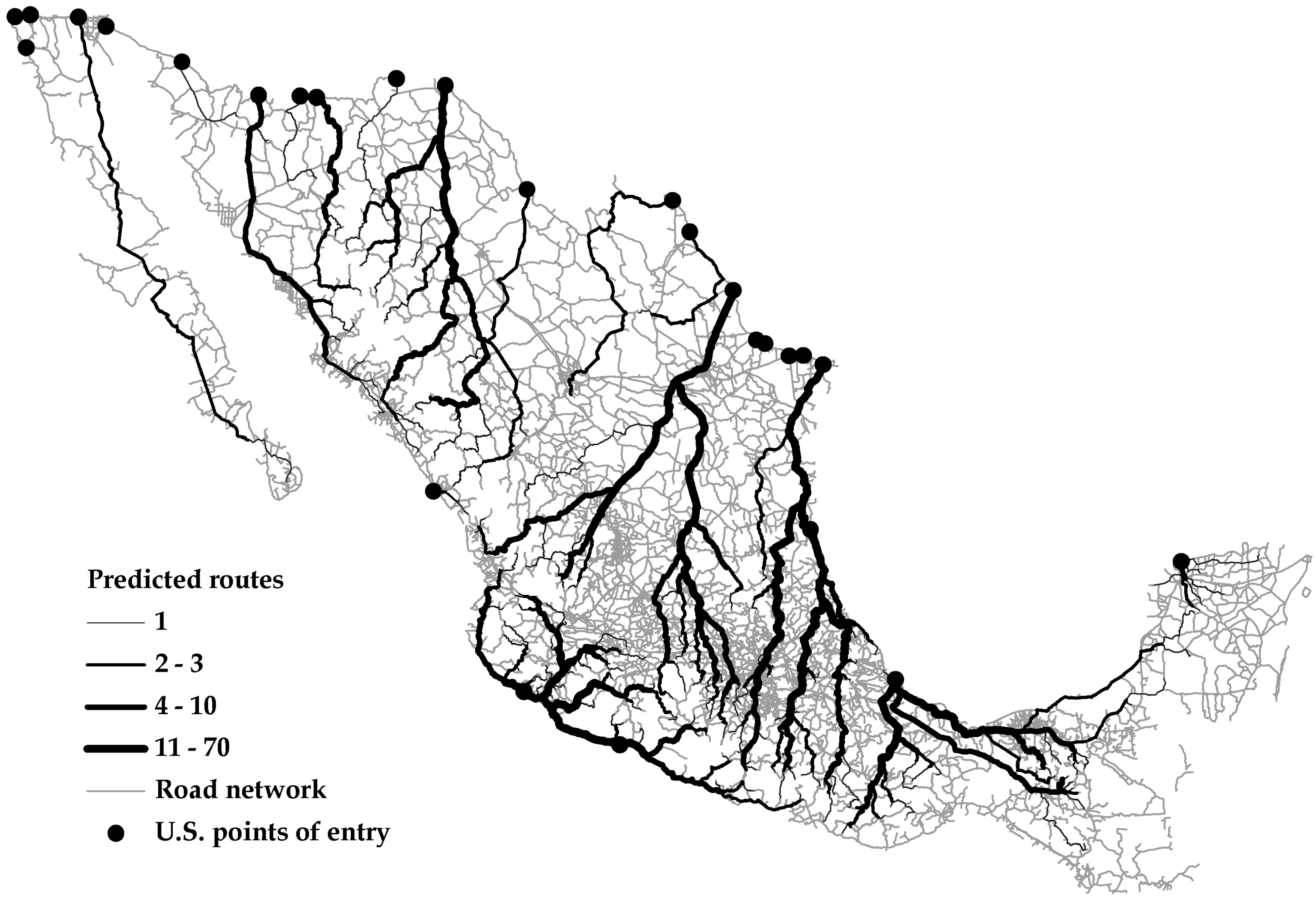


(c) Close PAN victory increases costs; routes change



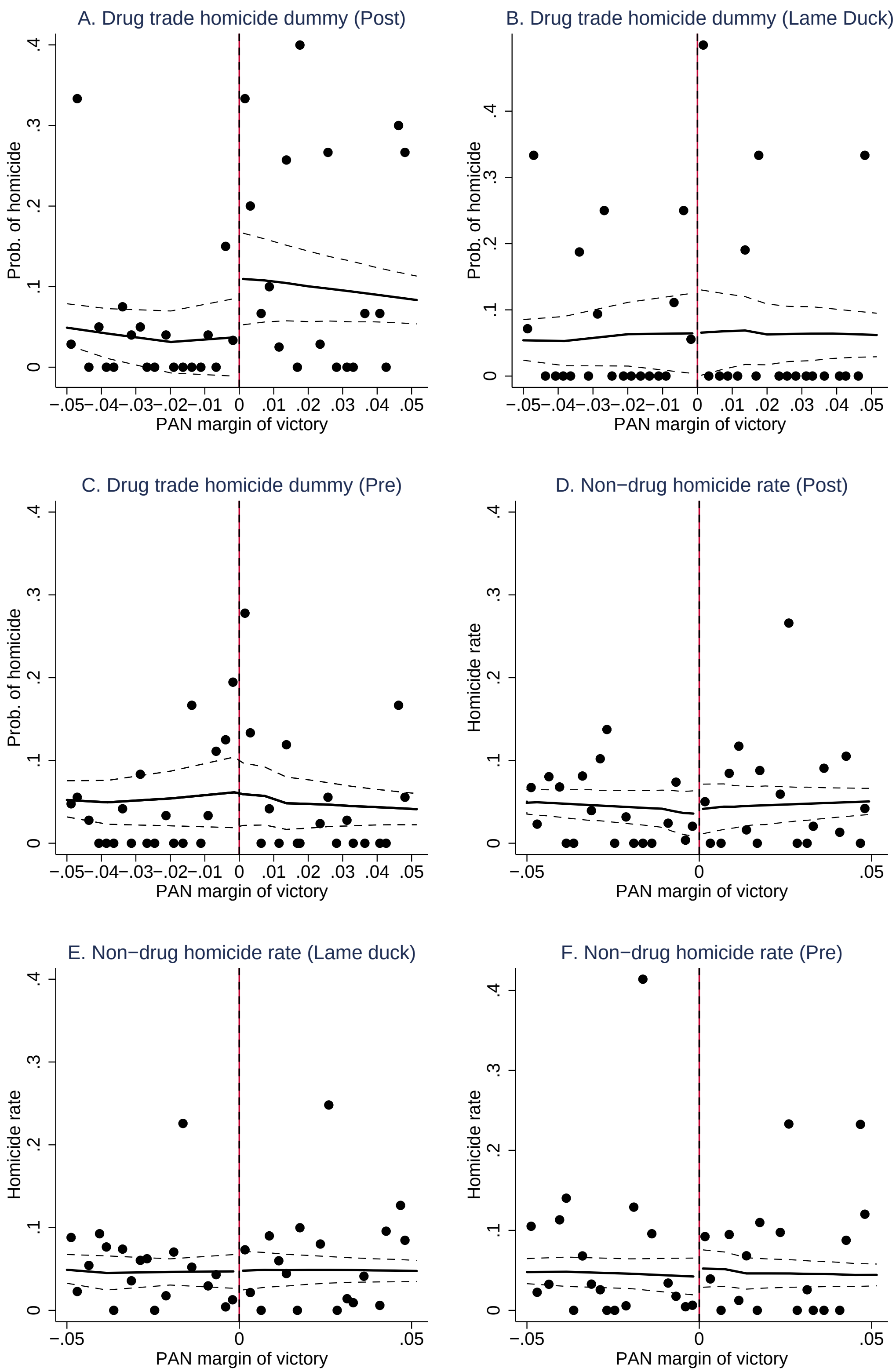
(d) Do confiscation patterns also change?

Figure 2: Road Network and Predicted Trafficking Routes



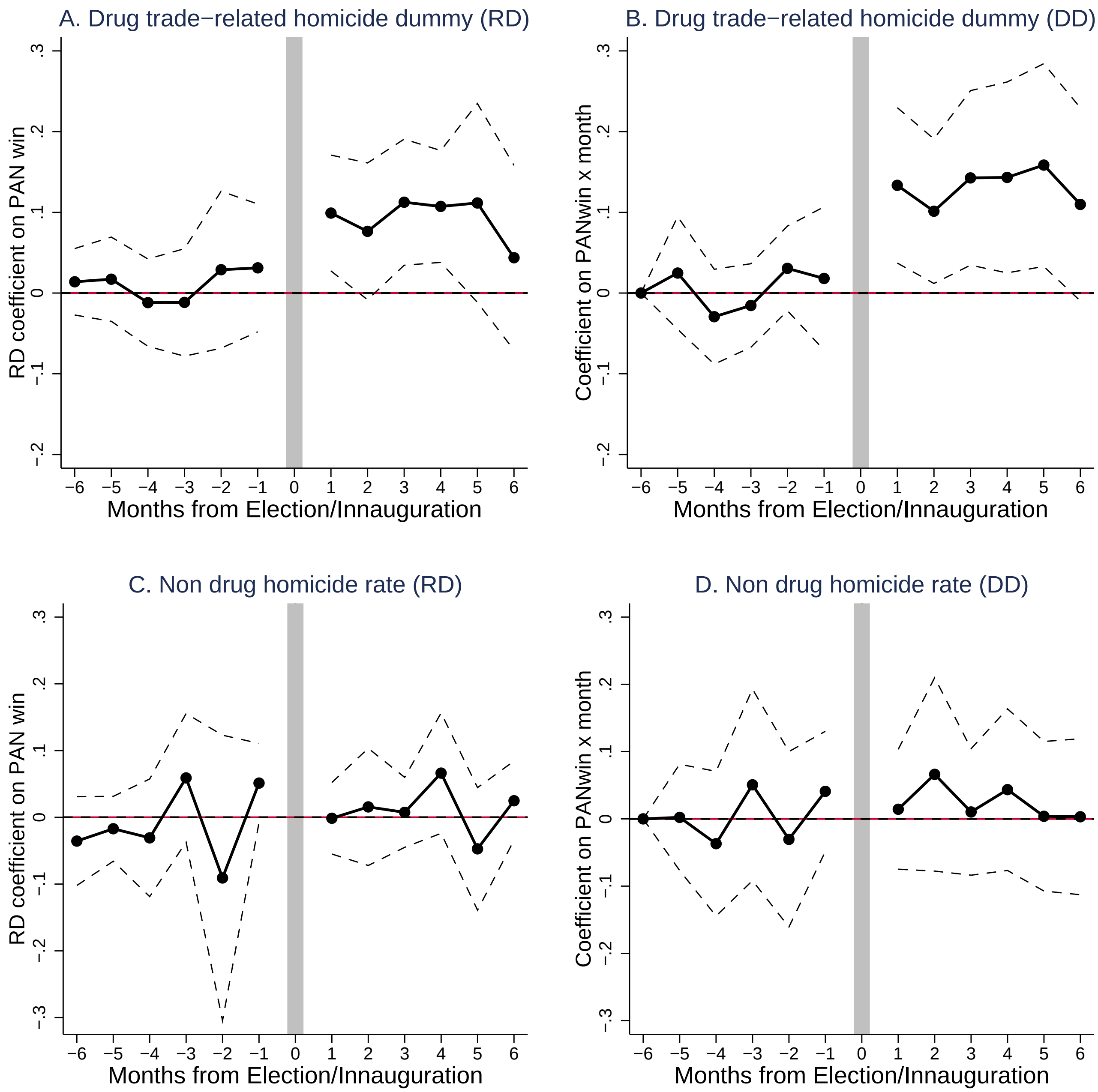
Notes: The least cost routes plotted in this figure are predicted using the network model with congestion costs.

Figure 3: RD Results: Close PAN Victories and Violence



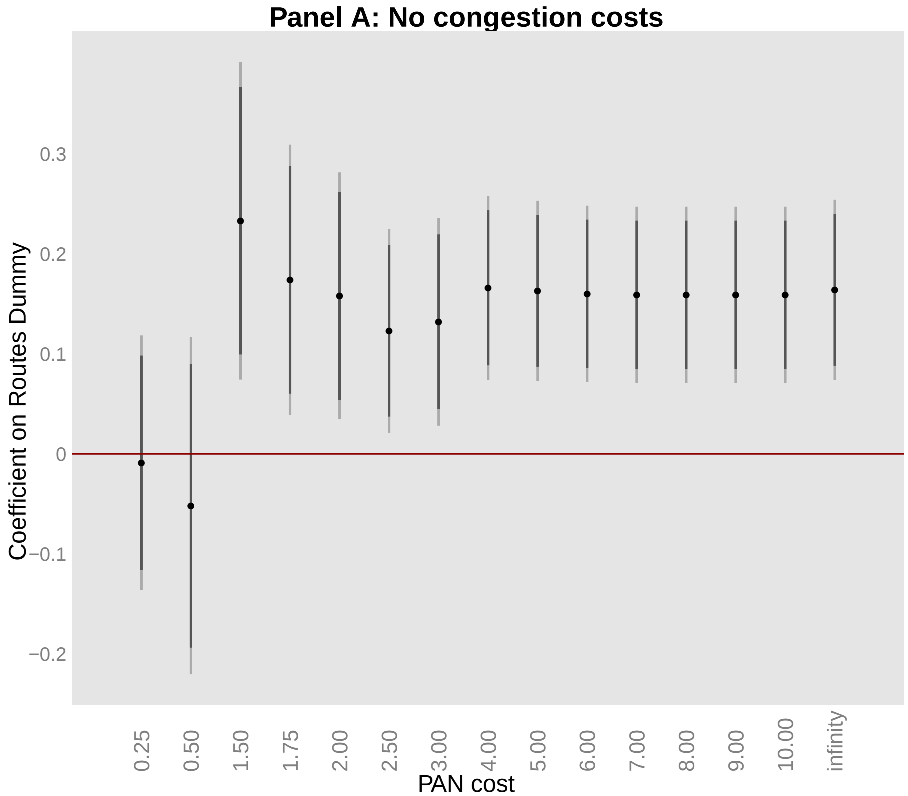
Notes: This figure plots violence measures against the PAN margin of victory, with a negative margin indicating a PAN loss. Each point represents the average value of the outcome in vote spread bins of width 0.0025. The solid line plots predicted values from a local linear regression, with separate vote 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).

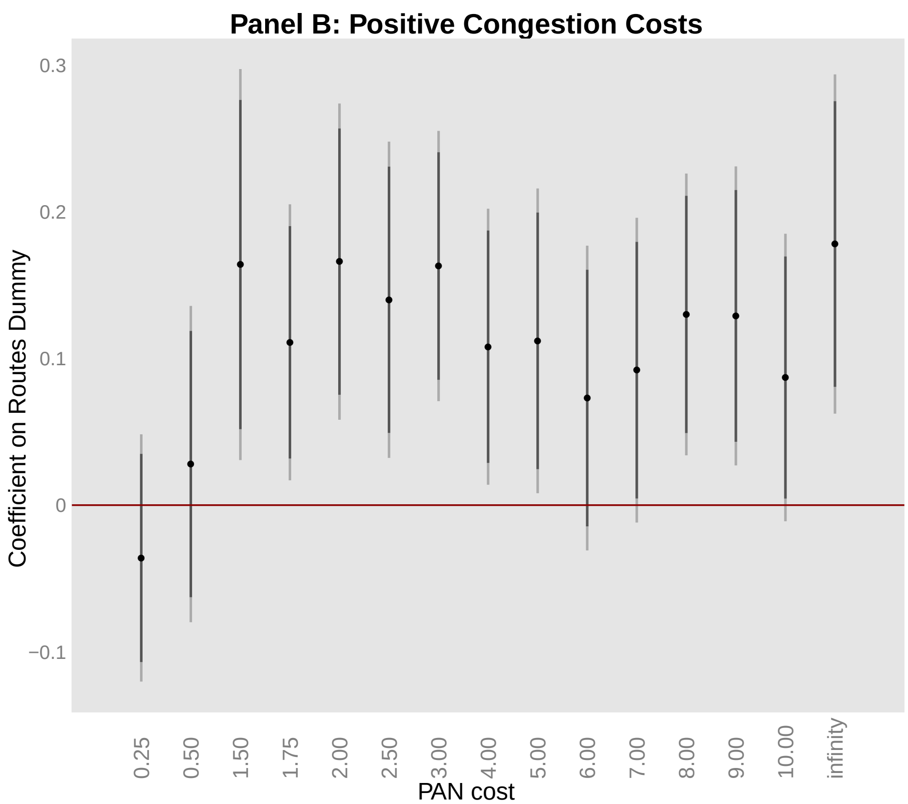
Figure 4: Estimates by Month



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.

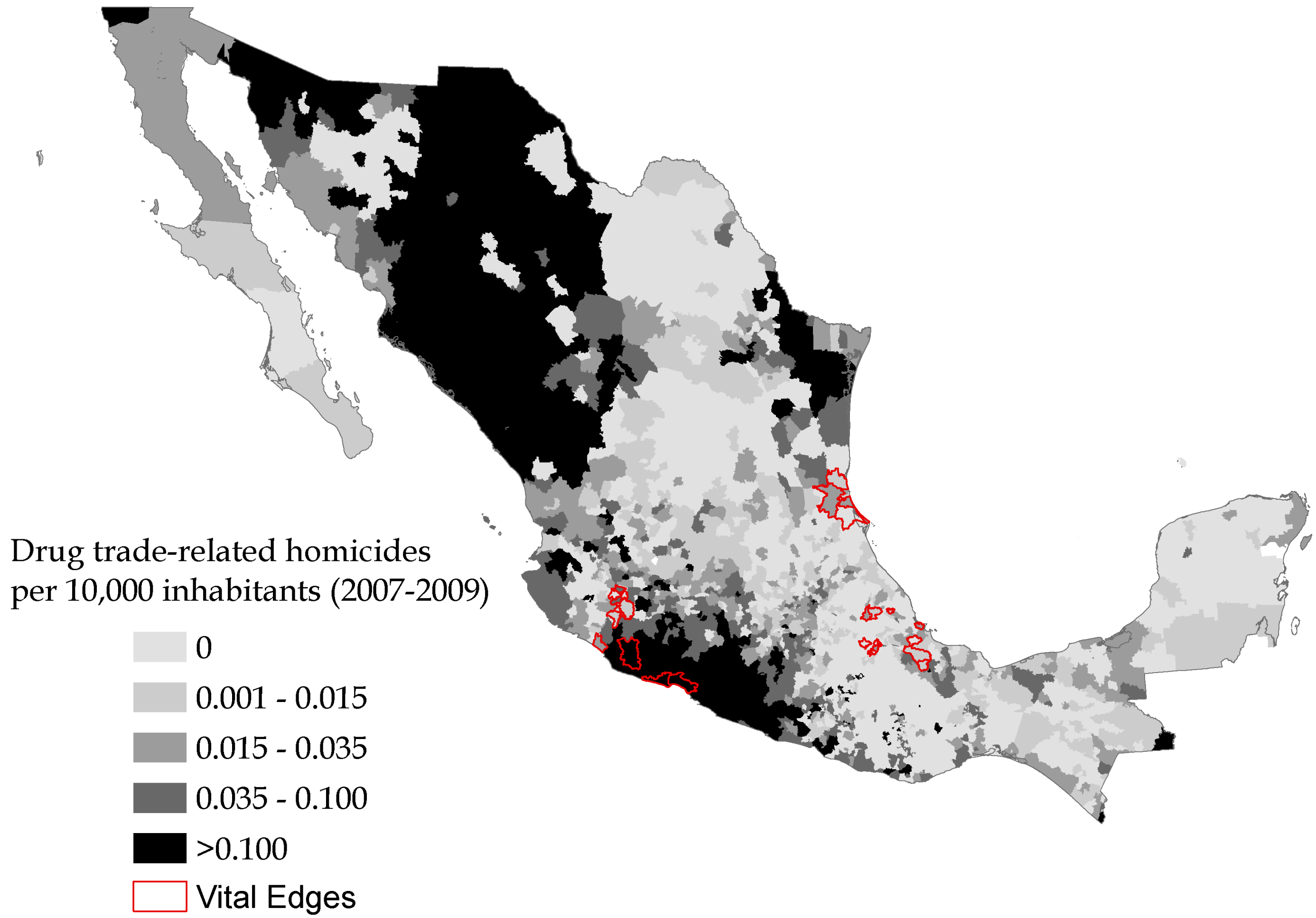
Figure 5: Varying the Costs Imposed by PAN Victories





Notes: The y-axis plots the coefficient on the routes dummy in equation (5) when a close PAN victory is assumed to proportionately increase the effective length of edges in the municipality by a factor of α. The x-axis plots values of α ranging from 0.25 to 10. 95% confidence bands are shown with a thin black line and 90% confidence bands with a slightly thicker black line.

Figure 6: Vital Edges



Notes: Municipalities that contain a vital edge are highlighted in red. The average monthly drug trade-related homicide rate between 2007 and 2009 is plotted in the background.