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A-1 Estimation appendix

A-1.1 The shortest paths problem

The model setup is as follows: 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. Traffickers transport drugs across the network from a set of origins to a set of destinations. Trafficking paths connect origins to destinations. 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. Close PAN victories remove edges from the network. Let $\mathcal{P}_i$ denote the set of all possible paths between producing municipality i and the United States. Each trafficker solves:

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

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).

A-1.2 Solving for the congested trafficking equilibrium

An equilibrium routing pattern must satisfy the following conditions (Wardrop, 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 $x_p > 0\ x_{p'} = 0$, $\sum_{e \in p'} c_e(x_e, l_e) \geq \sum_{e \in p} c_e(x_e, l_e)$.

where x_p is total flows on path p, x_e is total flows on edge e, and $c_e(\cdot)$ is the cost to traverse edge 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. Specifically, the routing pattern $\mathbf{x}^*$ is an equilibrium if and only if it is a solution to:

$$\min \sum_{e \in E} \int_0^{x_e} c_e(z) dz \tag{A-2}$$

$$s.t. \quad \sum_{p \in \mathcal{P} | e \in p} x_p = x_e \quad \forall e \in E \tag{A-3}$$

$$\sum_{p \in \mathcal{P}_i} x_p = 1 \quad \forall i = 1, 2, \ldots, \quad \forall p \in \mathcal{P} \tag{A-4}$$

$$x_p \geq 0 \quad \forall p \in \mathcal{P} \tag{A-5}$$

The first constraint requires that the flow of traffic on the paths traversing an edge sum to the total flow of traffic on that edge, the second constraint requires that supply (equal to 1 for each producer i) be conserved, and the third constraint requires flows to be non-negative. By Weierstrass's Theorem, a solution to the above problem exists, and thus a trafficking equilibrium always exists.

While this problem does not have a closed-form solution, for a given network 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 simplex algorithm to non-linear programming problems. The Frank-Wolfe algorithm alternates between solving a linear program defined by a tangential approximation of the objective function in (A-2) and a line search that minimizes the objective over the line segment connecting the current iterate and the solution to the linear programming problem. The linear subproblem determines the direction of movement, and the line search selects the optimal step length in that direction. At the end of each iteration, the current iterate is updated to the $\mathbf{x_e}$ selected by the line search problem. The linear subproblem defines a lower bound on the optimal value, which is used in the termination criterion.

The tangential approximation to the objective given in (A-2) is a simple shortest paths problem in which the costs to traverse each edge $c_e(x_e, l_e)$ are evaluated at the current iterate's flows x_e^k. In other words, the linear subproblem finds the shortest path between each producing municipality and the nearest U.S. point of entry given edge costs of $c_e(x_e^k, l_e)$ at iteration k. The linear subproblem is solved using Dijkstra's algorithm (Dijkstra, 1959). The line search problem is solved using the golden section method (Kiefer, 1953).

A-1.3 Moments

In the baseline congestion model, the moments match the mean model predicted and observed confiscations at ports, at terrestrial bordering crossings, and on interior edges. 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. Finally, the moment conditions match the model predicted and observed variance of confiscations across U.S. points of entry and across interior edges. For the congestion models reported in the appendix that estimate six separate crossing congestion parameters, the moment conditions match mean model predicted and observed confiscations for each of the six separate groups of crossings, instead of matching mean confiscations for all ports and for all terrestrial border crossings.

The model with DTO territorial costs and no congestion matches mean confiscations, mean confiscations interacted with DTO presence, and mean confiscations interacted with the share of Mexico's territory (if any) that the municipality's DTO controls. The model that includes congestion matches the same moments as in the baseline congestion model as well as the two moments that interact confiscations and DTO presence/share.

The model with a PAN cost parameter and no congestion matches the mean monthly change in confiscations in municipalities that do not have a PAN mayor elected during the Calderón period. The sample is limited to these municipalities because it is plausible that enforcement remains constant. The model also matches the mean monthly change in confiscations in municipalities bordering a municipality with a PAN mayor elected during the sample period. These municipalities are useful for estimating the PAN cost parameter because drug traffic is often diverted to them. The model that includes both a PAN cost parameter and congestion matches the same moments as in the baseline congestion model, as well as the two moments that summarize changes in confiscations.

A-1.4 Maximizing the simulated method of moments objective function

The simulated method of moments (SMM) estimator $\hat{\theta}$ minimizes a weighted quadratic form:

$$\theta = \underset{\theta \in \Theta}{\operatorname{argmin}} \frac{1}{M} \left[\sum_{m=1}^{M} \hat{g}(X_m, \theta) \right]' \Sigma \left[\sum_{m=1}^{M} \hat{g}(X_m, \theta) \right] \tag{A-6}$$

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.

The SMM objective function is not globally convex, and thus standard gradient methods may perform poorly. Instead, I use simulated annealing (Kirkpatrick, Gelatt, and Vecchi, 1983), which is more suitable for problems that lack a globally convex objective.[1] Simulated annealing is a non-gradient iterative method that differs from gradient methods in permitting

[1] See Goffe, Ferrier, and Rogers (1994) for a comprehensive review and Cameron and Trivedi (2005, p. 347) for a textbook treatment.

movements that increase the objective function being minimized.

Given a value of $\hat{\theta}_s$ for the congestion parameters at the sth iteration, the algorithm perturbs the jth component of $\hat{\theta}_s$ so as to obtain a new trial value of $\theta_s^* = \hat{\theta}_s + [0 \dots 0\ (\lambda_s r_s)\ 0 \dots 0]'$, where λ_s is a pre-specified step length and r_s is a draw from a uniform distribution on $(-1, 1)$. The method sets $\hat{\theta}_{s+1} = \theta_s^*$ if the perturbation decreases the objective function. If θ_s^* does not decrease the objective, it is accepted with probability $\frac{1}{1+exp\left(\frac{\Delta}{T_s}\right)}$, where Δ is the change in value of the objective and T_s is a positive scaling parameter called the temperature. Uphill moves are accepted with a probability that declines with the change in the objective function and increases with the temperature.[2] The temperature is set to T_0 at the initial iteration and updated according to the temperature schedule $T_k = T_0/k$. The annealing parameter k is initially set equal to the iteration number. If after a given number of iterations convergence has not been achieved, k is set to some value less than the iteration number so that the temperature increases and the algorithm can move to a potentially more promising region of the parameter space. The dependency between the temperature and acceptance probability is such that the current solution changes almost randomly when T is large and increasingly downhill as T goes to zero.

The algorithm runs until the average change in value of the objective function over a given number of iterations is less than some small number ϵ. I choose the starting value using a grid search over the parameter space. Results (available upon request) are robust to the use of different starting values and annealing parameters, with these choices primarily affecting the speed with which the algorithm converges.

A-1.5 Inference

Predicted confiscations on a given edge are not independent of predicted confiscations elsewhere in the network, introducing spatial dependence. Conley (1999) explores method of moments estimators for data exhibiting spatial dependence, showing that the sufficient conditions for consistency and normality require the dependence amongst observations to die away as the distance between the observations increases. This condition appears likely to hold in the current application, since drugs are typically trafficked to relatively close crossings. With the presence of spatial dependence, the asymptotic covariance matrix Λ is replaced by a weighted average of spatial autocovariance terms with zero weights for observations farther than a certain distance (Conley, 1999):

$$\hat{\lambda} = \frac{1}{M} \sum_m \sum_{s \in Mun_m} [\hat{g}(X_m, \theta)\hat{g}(X_m, \theta)'] \tag{A-7}$$

[2] Since both Δ and T_s are positive, the probably of acceptance is between zero and one half.

where Mun_m is the set of all municipalities within 250 kilometers of municipality m, including municipality m. The implicit assumption is that the correlation between observations is negligible for municipalities beyond 250 kilometers.

A-1.6 The government's resource allocation problem

To apply the trafficking framework to policy analysis, I embed the trafficking model in a Stackelberg network game (Baş and Srikant, 2002). In the first stage, the government (a single player) decides how to allocate law enforcement resources to edges in the road network, subject to a budget constraint. The edges selected by the government are referred to as vital edges. Traffickers' costs of traversing an edge increase when law enforcement resources are placed on it. The network model best predicts the diversion of drug traffic following PAN victories 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.[3] With more information on the resources deployed in PAN crackdowns, it would be possible to construct more precise estimates of the costs that law enforcement resources impose on traffickers.

In the second stage, traffickers simultaneously select least cost routes to the U.S. The government's objective is to maximize the total costs that traffickers incur, and each trafficker minimizes his own costs. 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.

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,

[3] 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.

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 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.[4] 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.

Appendix Figure A17 plots the results of this exercise with $k = 25$ and $N = 250$, highlighting municipalities that contain a vital edge in yellow. 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 0.043 percent and increases total trafficking costs by 17 percent. Appendix Table A16 documents that 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 $k = 2 \dots 25$.

[4] 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.

References

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

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

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

Cameron, A. (2005): *Microeconometrics: methods and applications*, Cambridge university press.

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

Goffe, W., G. Ferrier, and J. Rogers (1994): "Global optimization of statistical functions with simulated annealing," *Journal of Econometrics*, 60, 65–99.

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

Kiefer, J. (1953): "Sequential minimax search for a maximum," in *Proceedings of the American Mathematical Society*, vol. 4, 502–506.

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

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

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

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

A-2 Additional Results

- **Table A-1:** Means comparisons for baseline characteristics that limit the sample to municipalities with a vote spread of four, three, or two percentage points or less (analogous to Table 1 in the main text)
- **Table A-2:** RD comparisons for baseline characteristics that limit the sample to municipalities with a vote spread of four, three, or two percentage points or less (analogous to Table 1 in the main text)
- **Table A-3:** RD results that include municipalities with less than six months of pre-period data (analogous to Table 2 in the main text)
- **Table A-4:** RD results for non-drug trade-related homicides (analogous to Table 2 in the main text)
- **Table A-5:** RD results using alternative vote spread bandwidths (analogous to Table 2 in the main text)
- **Table A-6:** Local politics and violence using a panel data specification (analogous to Table 3 in the main text)
- **Table A-7:** The organization of drug trafficking and violence using a panel data specification and alternative functional forms for the RD polynomial (analogous to Table 4 in the main text)
- **Table A-8:** Spillovers results using the count measure of predicted trafficking routes (analogous to Table 5 in the main text)
- **Table A-9:** Spillovers results including post x initial party trends (analogous to Tables 5 and 6 in the main text)
- **Table A-10:** Reduced form spillover results
- **Table A-11:** SMM parameter estimates
- **Table A-12:** Drug traffic spillovers using the congestion cost parameters reported in Columns (2) and (3) of Table A-11 (analogous to Table 5 in the main text)
- **Table A-13:** Violence spillovers using the congestion cost parameters reported in Columns (2) and (3) of Table A-11 (analogous to Table 6 in the main text)

- **Table A-14:** Spillovers results using extensions of the trafficking model (analogous to Tables 5 and 6 in the main text)
- **Table A-15:** Labor market spillovers
- **Table A-16:** Robustness of the policy algorithm
- **Figure A-1:** A map showing municipalities with close elections
- **Figure A-2 - A-9:** RD plots for each baseline characteristic in Table 1
- **Figure A-10:** Vote spread density
- **Figure A-11:** RD plot for the drug trade-related homicide rate (analogous to Figure 3 in the main text)
- **Figure A-12:** Close PAN victories and violence during the year following the inauguration of new authorities
- **Figure A-13:** RD results including municipalities with less than six months of pre-period data (analogous to Figure 3 in the main text)
- **Figure A-14:** Close election outcomes and subsequent homicides between 2004 and 2006
- **Figure A-15:** Spillovers results assuming that PAN victories impose non-infinite costs
- **Figure A-16:** Spillovers placebo exercise
- **Figure A-17:** The allocation of law enforcement

Table A-1: Baseline characteristics: means comparisons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	4% vote spread			3% vote spread			2% vote spread		
	PAN won	PAN lost	t stat difference	PAN won	PAN lost	t stat difference	PAN won	PAN lost	t stat difference
Crime characteristics									
Drug-trade related homicides	0.04	0.05	(-0.58)	0.04	0.06	(-0.51)	0.06	0.08	(-0.38)
Confrontation deaths	0.05	0.06	(-0.18)	0.06	0.08	(-0.26)	0.09	0.1	(-0.16)
Annual homicide rate (1990-2006)	1.41	1.52	(-0.33)	1.52	1.55	(-0.06)	1.35	1.61	(-0.80)
Municipal political characteristics									
Mun. taxes per capita (2005)	64.52	50.13	(0.96)	67.85	48.18	(1.13)	82.31	50.58	(1.32)
Turnout	0.61	0.59	(0.58)	0.6	0.6	(0.27)	0.6	0.58	(0.48)
PAN incumbent	0.26	0.29	(-0.34)	0.23	0.3	(-0.82)	0.27	0.28	(-0.03)
PRD incumbent	0.16	0.13	(0.54)	0.21	0.11	(1.32)	0.15	0.14	(0.15)
% alternations (1976-2006)	0.31	0.31	(-0.10)	0.32	0.3	(0.45)	0.32	0.31	(0.21)
PRI never lost (1976-2006)	0.08	0.08	(0.03)	0.08	0.11	(-0.41)	0.09	0.14	(-0.57)
Demographic characteristics									
Population (2005)	6.48	5.12	(0.45)	7.87	5.64	(0.58)	10.06	5.43	(0.89)
Population density (2005)	197.63	210.49	(-0.16)	218.11	249.33	(-0.30)	257.93	313.69	(-0.36)
Migrants per capita (2005)	0.02	0.02	(-0.80)	0.02	0.02	(-0.50)	0.02	0.02	(-0.19)
Economic characteristics									
Income per capita (2005)	4.37	4.4	(-0.06)	4.46	4.43	(0.05)	4.65	4.88	(-0.32)
Malnutrition (2005)	32.18	31.52	(0.20)	30.77	31.24	(-0.12)	30.11	26.33	(0.83)
Mean years schooling (2005)	6.23	6.17	(0.22)	6.39	6.24	(0.49)	6.49	6.58	(-0.24)
Infant mortality (2005)	22.35	21.97	(0.30)	22	22.03	(-0.02)	22.25	20.9	(0.74)
HH w/o access to sewage (2005)	8.05	8.23	(-0.13)	8.33	8.06	(0.16)	8.17	7.22	(0.49)
HH w/o access to water (2005)	17.15	15.93	(0.33)	18.75	16.24	(0.56)	17.49	14.63	(0.53)
Marginality index (2005)	-0.16	-0.12	(-0.26)	-0.2	-0.12	(-0.41)	-0.27	-0.28	(0.03)
Road network characteristics									
Detour length (km)	30.92	26.28	(0.19)	38.31	34.56	(0.12)	48.09	55.16	(-0.15)
Road density ($/^2$)	0.15	0.13	(0.90)	0.15	0.15	(0.27)	0.17	0.15	(0.48)
Distance U.S. (km)	708.09	765.78	(-1.05)	680.18	770.18	(-1.57)	654.64	740.4	(-1.13)
Geographic characteristics									
Elevation (m)	1368.73	1416.56	(-0.31)	1438.28	1404.29	(0.19)	1471.42	1337.41	(0.62)
Slope (degrees)	3.63	3.42	(0.44)	3.67	3.62	(0.09)	3.66	3.34	(0.46)
Surface area (km^2)	1951.44	535.23	(1.59)	2246.8	448.9	(1.60)	2788.02	528.14	(1.39)
Average min. temperature, C	11.91	12.19	(-0.31)	11.32	12.31	(-0.96)	10.98	12.48	(-1.22)
Average max. temperature, C	26.44	26.71	(-0.42)	25.99	26.58	(-0.80)	25.65	26.95	(-1.46)
Average precipitation, cm	114.7	101.21	(1.04)	110.43	103.52	(0.49)	106.81	96.81	(0.62)
Observations	61	62		48	46		33	29	

Notes: See Table 1 for sources. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A-2: Baseline characteristics: local linear regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	5% vote spread		4% vote spread		3% vote spread		2% vote spread	
	RD estimate	t-stat	RD estimate	t-stat	RD estimate	t-stat	RD estimate	t-stat
Crime characteristics								
Drug-trade related homicides	-0.01	(-0.20)	-0.01	(-0.19)	-0.02	(-0.24)	-0.03	(-0.24)
Confrontation deaths	-0.04	(-0.33)	-0.05	(-0.38)	-0.07	(-0.48)	-0.09	(-0.45)
Annual homicide rate (1990-2006)	-0.01	(-0.02)	-0.04	(-0.09)	-0.11	(-0.19)	0.26	(0.33)
Political characteristics								
Mun. taxes per capita (2005)	47.24	(1.37)	47.37	(1.23)	47.21	(0.97)	52.83	(0.78)
Turnout	0.02	(0.41)	0.02	(0.45)	0.04	(0.60)	0.05	(0.64)
PAN incumbent	-0.01	(-0.07)	0.01	(0.07)	0.02	(0.12)	-0.02	(-0.06)
PRD incumbent	0.01	(0.10)	0	(-0.03)	-0.03	(-0.23)	-0.02	(-0.10)
% alternations (1976-2006)	0.05	(0.91)	0.06	(0.98)	0.07	(1.05)	0.1	(1.20)
PRI never lost (1976-2006)	-0.12	(-1.13)	-0.14	(-1.28)	-0.17	(-1.47)	-0.21	(-1.64)
Demographic characteristics								
Population (2005)	5.11	(0.77)	4.86	(0.68)	2.81	(0.33)	0.87	(0.07)
Population density (2005)	-258.84	(-1.23)	-309.67	(-1.35)	-475.59	(-1.79)*	-715.75	(-1.92)*
Migrants per capita (2005)	0	(-0.28)	0	(-0.30)	0	(-0.74)	-0.01	(-0.86)
Economic characteristics								
Income per capita (2005)	-0.19	(-0.21)	-0.31	(-0.31)	-0.57	(-0.46)	-0.55	(-0.33)
Malnutrition (2005)	0.95	(0.16)	1.32	(0.21)	2.62	(0.36)	-1.14	(-0.13)
Mean years schooling (2005)	-0.28	(-0.52)	-0.43	(-0.74)	-0.87	(-1.28)	-1.1	(-1.19)
Infant mortality (2005)	0.8	(0.32)	1.11	(0.40)	1.81	(0.55)	2.01	(0.46)
HH w/o access to sewage (2005)	0.24	(0.11)	0.05	(0.02)	-1.09	(-0.42)	-2.06	(-0.60)
HH w/o access to water (2005)	-0.04	(-0.01)	-3.5	(-0.55)	-7.09	(-1.08)	-7.49	(-1.04)
Marginality index (2005)	-0.08	(-0.27)	-0.08	(-0.26)	0.02	(0.06)	0.08	(0.16)
Road network characteristics								
Detour length (km)	-30.65	(-0.66)	-42.83	(-0.95)	-63.4	(-1.59)	-64.06	(-1.69)*
Road density (km/km^2)	-0.03	(-0.78)	-0.05	(-1.05)	-0.09	(-1.66)*	-0.15	(-2.31)**
Distance U.S. (km)	-143.78	(-1.35)	-138.25	(-1.18)	-106.69	(-0.76)	-138.26	(-0.75)
Geographic characteristics								
Elevation (m)	295.04	(0.94)	388.83	(1.13)	394.5	(0.98)	405.11	(0.79)
Slope (degrees)	-0.06	(-0.07)	-0.06	(-0.06)	-0.25	(-0.24)	-0.68	(-0.52)
Surface area (km^2)	2338.02	(1.85)*	2120.27	(1.91)*	1498.72	(1.43)	1136	(0.59)
Average min. temperature, C	-2.84	(-1.55)	-3.31	(-1.64)	-3.28	(-1.37)	-4.07	(-1.32)
Average max. temperature, C	-2.07	(-1.57)	-2.38	(-1.64)	-2.39	(-1.41)	-2.69	(-1.24)
Average precipitation, cm	1.98	(0.09)	0.88	(0.04)	5.69	(0.24)	2.61	(0.09)
Observations	152		123		94		62	

Notes: See Table 1 for sources. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A-3: Close PAN Elections and Violence (Larger Sample)

	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	0.071***	-0.002	0.010	0.078***	0.081**		0.105***		0.126***		0.155***	
	(0.023)	(0.027)	(0.012)	(0.024)	(0.037)		(0.031)		(0.040)		(0.050)	
PAN win						0.009		0.002		0.047		0.044
× lame duck						(0.053)		(0.054)		(0.079)		(0.080)
PAN win						0.125***		0.117***		0.186***		0.186***
× post-inaug.						(0.043)		(0.041)		(0.055)		(0.055)
Panel B: Drug trade-related homicide rate												
PAN win	0.041**	0.008	0.004	0.040**	0.040**		0.053**		0.079**		0.080**	
	(0.017)	(0.021)	(0.005)	(0.017)	(0.020)		(0.026)		(0.032)		(0.033)	
PAN win						0.023		0.017		0.062*		0.062*
× lame duck						(0.022)		(0.023)		(0.034)		(0.034)
PAN win						0.077**		0.076**		0.093**		0.090**
× post-inaug.						(0.033)		(0.033)		(0.037)		(0.036)
Clusters						176		176		176		176
Observations	506	506	506	506	506	2,072	506	2,072	506	2,072	506	2,072

Notes: In columns (1), (4), (5), (7), (9), and (11) the dependent variable is the average monthly drug related homicide probability (Panel A) or rate (Panel B) in the post-inauguration period; in column (2) it is average drug related homicides in the lame duck period, and in column (3) it is average drug related homicides in the pre-election period. In columns (6), (8), (10), and (12), it is the drug related homicide dummy (rate) in a given municipality-month. All other variables are defined as in Table 2. 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. 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 A-4: Close PAN Elections and Non-Drug 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 non-drug trade-related homicides												
PAN win	-0.004	-0.028	0.043	-0.011	0.014		0.008		-0.010		-0.011	
	(0.032)	(0.047)	(0.030)	(0.033)	(0.053)		(0.042)		(0.052)		(0.069)	
PAN win						-0.046		-0.035		-0.107		-0.108
× lame duck						(0.068)		(0.066)		(0.089)		(0.087)
PAN win						-0.049		-0.035		-0.084		-0.097
× post-inaug.						(0.059)		(0.059)		(0.071)		(0.068)
Panel B: Non-drug trade-related homicide rate												
PAN win	0.003	-0.000	0.007	-0.004	0.008		0.009		0.006		0.011	
	(0.022)	(0.035)	(0.022)	(0.021)	(0.022)		(0.031)		(0.042)		(0.051)	
PAN win						0.028		0.028		-0.025		-0.025
× lame duck						(0.061)		(0.056)		(0.061)		(0.059)
PAN win						0.008		0.010		-0.020		-0.027
× post-inaug.						(0.053)		(0.052)		(0.057)		(0.055)
Clusters						141		141		141		141
Observations	395	395	395	395	395	1,825	395	1,825	395	1,825	395	1,825

Notes: In columns (1), (4), (5), (7), (9), and (11) the dependent variable is the average monthly non-drug related homicide probability (Panel A) or rate (Panel B) in the post-inauguration period; in column (2) it is average non-drug related homicides in the lame duck period, and in column (3) it is average non-drug related homicides in the pre-election period. In columns (6), (8), (10), and (12), it is the non-drug related homicide dummy (rate) in a given municipality-month. All other variables are defined as in Table 2. 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. 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 A-5: Alternative Bandwidths

	Absolute vote spread less than:					
	5%	4%	3%	5%	4%	3%
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Linear functional form						
PAN win	0.142***	0.186***	0.211***			
	(0.032)	(0.037)	(0.047)			
PAN win				0.019	0.028	0.051
× lame duck				(0.058)	(0.067)	(0.078)
PAN win				0.147***	0.154***	0.162**
× post-inaug.				(0.051)	(0.054)	(0.062)
Panel B: Quadratic functional form						
PAN win	0.202***	0.197***	0.191**			
	(0.050)	(0.058)	(0.086)			
PAN win				0.007	0.022	0.046
× lame duck				(0.059)	(0.068)	(0.079)
PAN win				0.132***	0.152***	0.159***
× post-inaug.				(0.047)	(0.053)	(0.059)
Panel C: Cubic functional form						
PAN win	0.156**	0.152*	0.122			
	(0.071)	(0.091)	(0.120)			
PAN win				0.050	0.044	-0.018
× lame duck				(0.088)	(0.118)	(0.128)
PAN win				0.204***	0.196***	0.172**
× post-inaug.				(0.064)	(0.073)	(0.083)
Panel D: Quartic functional form						
PAN win	0.125	0.160	0.097			
	(0.102)	(0.118)	(0.195)			
PAN win				0.046	0.041	-0.008
× lame duck				(0.090)	(0.121)	(0.124)
PAN win				0.204***	0.196***	0.168**
× post-inaug.				(0.062)	(0.070)	(0.079)
Observations	149	120	93	1,960	1,584	1,214

Notes: In columns (1) through (3), the dependent variable is the average monthly drug related homicide probability in the post-inauguration period, and in columns (4) through (6), it is the drug related homicide dummy in a given municipality-month. The specifications in columns (1) through (3) also include state fixed effects and controls for baseline characteristics, estimated separately on either side of the PAN win-loss threshold. The specifications in columns (4) through (6) also 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 panel headings and the lame duck and post-inauguration dummies. Robust standard errors, clustered by municipality in columns (4) through (6), are in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A-6: Local Politics and Violence

	(1)	(2)	(3)	(4)	(5)	(6)
	Elections involving PAN			Alternative samples		
	Baseline	PAN Incumbent	PRI Opponent	PRI v. PRD	Any alternation	All muns.
PAN win x post-inaug.	0.132***	0.118**	0.137**			0.019**
	(0.047)	(0.048)	(0.066)			(0.008)
PAN win x post-inaug. x PAN Incumbent		0.068				
		(0.056)				
PAN win x post-inaug. x PRI opponent			-0.030			
			(0.052)			
PRI win x post-inaug.				0.060		
				(0.056)		
Alternate x post-inaug.					0.057*	
					(0.035)	
R^2	0.24	0.24	0.25	0.15	0.12	0.09
Clusters	152	152	152	136	365	1286
Observations	1960	1960	1960	1730	4680	14146
Mean dep. var.	0.065	0.065	0.065	0.052	0.058	0.060
Post-innaug. effect (PAN incumbent)		0.186***				
		(0.070)				
Post-innaug. effect (PRI opponent)			0.107**			
			(0.046)			

Notes: The dependent variable in all columns is a dummy variable equal to one if a drug trade-related homicide occurred in a given municipality-month and equal to zero otherwise. 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 include month x state and municipality fixed effects, a post-inauguration main effect, a lame duck main effect, and a quadratic polynomial in vote spread interacted with the lame duck and post-inauguration dummies. Column (2) contains a post-inauguration x PAN incumbent interaction, and column (3) contains a post-inauguration x PRI opponent interaction. The lame duck terms are omitted from the table to conserve space. In columns (1) through (5) the sample is limited to municipalities with a vote spread of five percentage points or less. 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. Robust standard errors, clustered by municipality, are in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A-7: 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 ×			0.513***		0.268							
borders rival			(0.180)		(0.233)							
PAN win ×			0.126*		0.172*							
borders allies			(0.071)		(0.095)							
PAN win ×			0.012		0.010							
local gang			(0.032)		(0.045)							
PAN win ×							0.070***		0.070***		0.070***	
detour							(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				0.401***		0.411***						
× borders rival				(0.116)		(0.111)						
PAN win × post				0.047		0.049						
× borders allies				(0.102)		(0.098)						
PAN win × post				0.009		0.019						
× local gang				(0.024)		(0.026)						
PAN win × post								0.150***		0.148***		0.144***
× detour								(0.024)		(0.022)		(0.021)
Vote spread terms	linear	linear	linear	linear	quad.	quad.	linear	linear	quad.	quad.	cubic	cubic
R-squared	0.648	0.247	0.633	0.271	0.646	0.274	0.671	0.279	0.675	0.282	0.676	0.283
Clusters		152		152		152		152		152		152
Observations	430	1,672	430	1,672	430	1,672	430	1,672	430	1,672	430	1,672
Borders rival			0.533***	0.524***	0.306	0.518***						
effect			(0.174)	(0.131)	(0.226)	(0.122)						
Borders allies			0.146**	0.169*	0.209**	0.157*						
effect			(0.069)	(0.092)	(0.090)	(0.091)						
Local gang			0.032	0.132**	0.047	0.127**						
effect			(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 A-8: The Diversion of Drug Traffic (Count Measure of Routes)

	(1)	(2)	(3)
	Full Sample	Limited Sample	Full Sample
	Domestic drugs		Cocaine
Panel A: Shortest Paths			
Predicted	0.022***	0.016*	0.006
routes	(0.008)	(0.009)	(0.006)
Panel B: Model with Congestion Costs			
Predicted	0.005	0.002	-0.003
routes	(0.004)	(0.004)	(0.002)
State x month FE	yes	yes	yes
Municipality FE	yes	yes	yes
R^2	0.47	0.47	0.37
Municipalities	1869	1574	1869
Observations	69,153	58,238	69,153

Notes: The dependent variable in columns (1) and (2) is the log value of domestic illicit drug confiscations (or 0 if no confiscations are made), and the dependent variable in column (3) is the log value of confiscated cocaine (or 0 if no confiscations are made). Column (2) limits 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 A-9: Including Post x Party Trends

	(1)	(2)	(3)	(4)
	Confiscations		Homicide	
	dummy	value	dummy	rate
Panel A: Shortest Paths				
Predicted	0.016***	0.170***	0.013***	0.021*
routes	(0.005)	(0.050)	(0.005)	(0.011)
Panel B: Model with Congestion Costs				
Predicted	0.014***	0.177***	0.015***	0.022
routes	(0.005)	(0.059)	(0.005)	(0.019)
State x month FE	yes	yes	yes	yes
Municipality FE	yes	yes	yes	yes
Post x party trends	yes	yes	yes	yes
Municipalities	1869	1869	1869	1869
Observations	69,153	69,153	69,153	69,153

Notes: The dependent variable is a dummy equal to 1 if domestic illicit drug confiscations were made in column (1), the log value of domestic illicit drug confiscations (or 0 if no confiscations were made) in column (2), an indicator equal to 1 if a drug trade-related homicide occurred in column (3), and the drug trade-related homicide rate per 10,000 inhabitants in column (4). All columns include month x state and municipality fixed effects as well as post x initial party trends. Standard errors clustered by municipality and month x state are reported in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A-10: Reduced Form Spillover Estimates

	(1)	(2)	(3)	(4)
	All muns	Borders mun with path and on detour	Borders mun with path and off detour	Doesn't border mun with path
PAN win	0.001	0.110*	0.018	-0.008
	(0.015)	(0.064)	(0.020)	(0.022)
R^2	0.601	0.812	0.679	0.501
Observations	1067	125	533	409

Notes: The dependent variable is the average probability that a drug trade-related homicide occurred in a given municipality-month during the post-inauguration period. All columns include state fixed effects and controls for baseline characteristics, estimated separately on either side of the PAN win-loss threshold. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A-11: 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 A-12: The Diversion of Drug Traffic (Alternative Parameters)

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample		Limited Sample		Full Sample	
	Domestic illicit drug confiscations				Cocaine confiscations	
	Dummy	Value	Dummy	Value	Dummy	Value
Panel A: Congestion Model (8 Parameters)						
Predicted	0.009**	0.114***	0.006	0.084*	0.003	0.014
routes dummy	(0.004)	(0.043)	(0.004)	(0.048)	(0.003)	(0.025)
Panel B: Congestion Model (10 Parameters)						
Predicted	0.011***	0.128***	0.009**	0.103**	0.002	0.014
routes dummy	(0.004)	(0.041)	(0.004)	(0.043)	(0.003)	(0.025)
State x month FE	yes	yes	yes	yes	yes	yes
Municipality FE	yes	yes	yes	yes	yes	yes
R^2	0.42	0.47	0.42	0.47	0.47	0.37
Municipalities	1869	1869	1574	1574	1869	1869
Observations	69,153	69,153	58,238	58,238	69,153	69,153
Mean dep. var.	0.053	0.589	0.055	0.613	0.046	0.163

Notes: The dependent variable in columns (1) and (3) is a dummy equal to 1 if domestic illicit drug confiscations are made in a given municipality-month; the dependent variable in columns (2) and (4) is the log value of domestic illicit drug confiscations (or 0 if no confiscations are made); the dependent variable in column (5) is a dummy equal to 1 if cocaine confiscations are made in a given municipality-month; and the dependent variable in column (6) is the log value of confiscated cocaine (or 0 if no confiscations are made). Columns (3) and (4) 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 A-13: Violence Spillovers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full Sample		Full Sample Drug-related homicide		Limited Sample		Full Sample Non-drug homicide
	dummy	dummy	rate	rate	dummy	rate	rate
Panel A: Congestion Model (8 Parameters)							
Predicted	0.013***		0.023**		0.012**	0.016	0.026*
routes dummy	(0.004)		(0.010)		(0.005)	(0.010)	(0.015)
One route		0.012*		0.019*			
		(0.006)		(0.010)			
More than		0.014***		0.026**			
one route		(0.005)		(0.012)			
Panel B: Congestion Model (10 Parameters)							
Predicted	0.009**		0.009		0.008**	0.001	0.023
routes dummy	(0.004)		(0.008)		(0.004)	(0.007)	(0.018)
One route		0.006		0.003			
		(0.005)		(0.009)			
More than		0.010**		0.012			
one route		(0.005)		(0.010)			
State x month FE	yes	yes	yes	yes	yes	yes	yes
Municipality FE	yes	yes	yes	yes	yes	yes	yes
R^2	0.36	0.36	0.10	0.10	0.35	0.09	0.07
Municipalities	1869	1869	1869	1869	1574	1574	1869
Observations	69,153	69,153	69,153	69,153	58,238	58,238	69,153
Mean dep.var.	0.044	0.028	0.044	0.028	0.045	0.026	0.117

Notes: The dependent variable in columns (1), (2), and (5) 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), and (6) 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 (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 A-14: Alternative Trafficking Models

	(1)	(2)	(3)	(4)	(5)	(6)
	No Congestion			Congestion		
	DTOs		Politics	DTOs		Politics
	Confiscations	Homicides	Homicides	Confiscations	Homicides	Homicides
Predicted routes	0.085*	0.008*	0.013***	0.105***	0.005*	0.012**
	(0.044)	(0.005)	(0.004)	(0.038)	(0.003)	(0.006)
State x month FE	yes	yes	yes	yes	yes	yes
Municipality FE	yes	yes	yes	yes	yes	yes
R^2						
Municipalities	1869	1869	1724	1869	1869	1724
Observations	69,153	69,153	63,788	69,153	69,153	63,788

Notes: The dependent variable in columns (1) and (4) is the log value of domestic illicit drug confiscations (or 0 if no confiscations are made). The dependent variable in columns (2), (3), (5), and (6) is an indicator equal to 1 if a drug trade-related homicide occurred in a given month. All columns include month x state and municipality fixed effects. Columns (1), (2), (4), and (5) omit municipalities that experienced a closed PAN victory, whereas columns (3) and (6) omit all municipalities that experienced a PAN victory. Standard errors clustered by municipality and month x state are reported in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A-15: Economic Spillovers

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

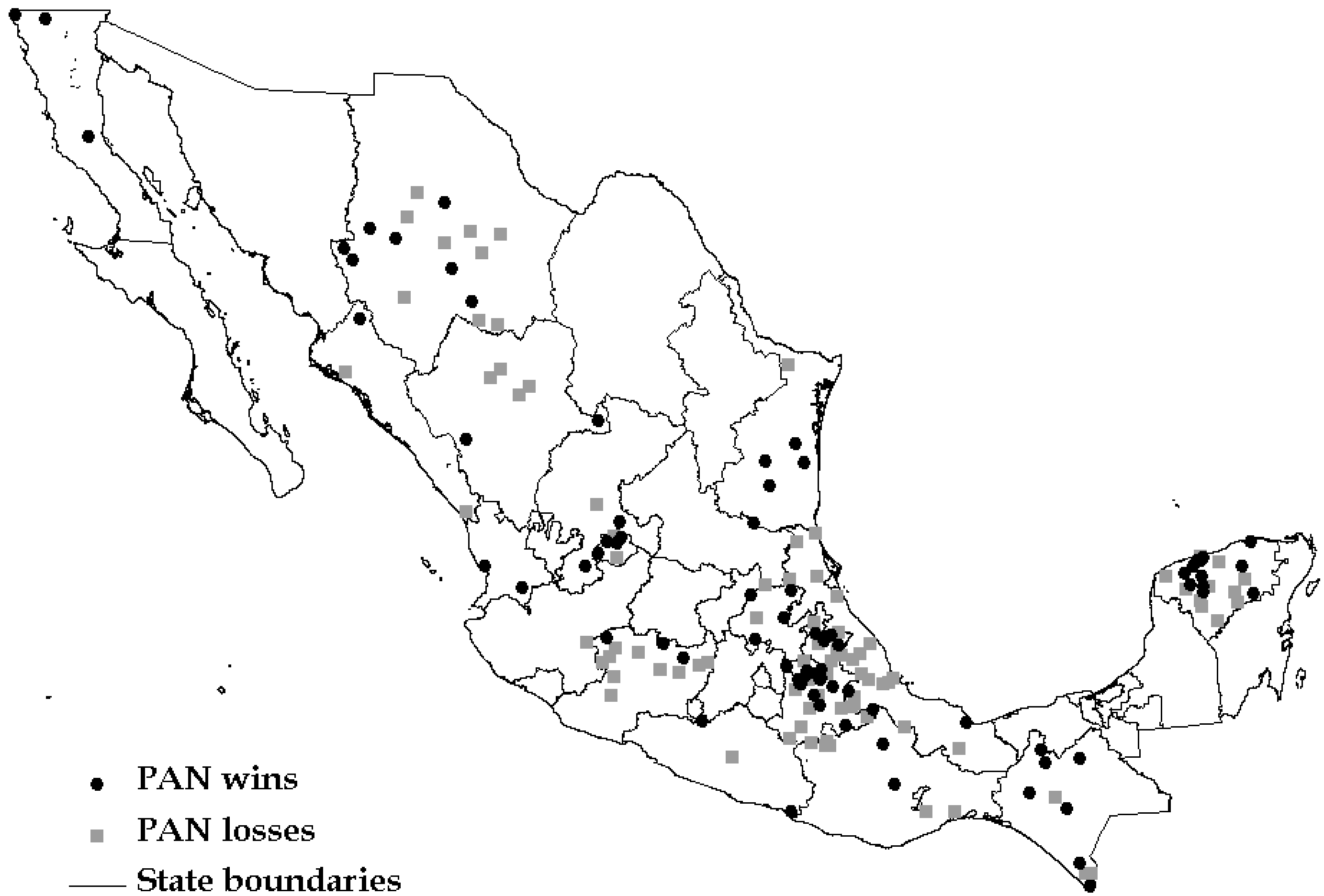
Notes: The dependent variable in column (1) is average municipal male labor force participation, the dependent variable in columns (2) and (5) is average municipal female labor force participation, the dependent variable in column (3) is log wages of formal sector workers, and the dependent variable in columns (4) and (6) is log wages of informal sector workers. 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) and (5) 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%.

Table A-16: Robustness of Policy Algorithm

	(1)
	Percentage increase in total costs
Baseline ($N = 250$)	0.168
$N = 100$	0.168
$N = 500$	0.168
Alternate between selecting edges with $m = 1$ and $m = 2$	0.105
Alternate between selecting edges with $m = 1$, $m = 2$, and $m = 3$	0.106
Select edge with $m = 2$ when $k = 1$	0.168
Select edge with $m = 3$ when $k = 1$	0.168
Select edge with $m = 4$ when $k = 1$	0.168
Select edge with $m = 5$ when $k = 1$	0.168

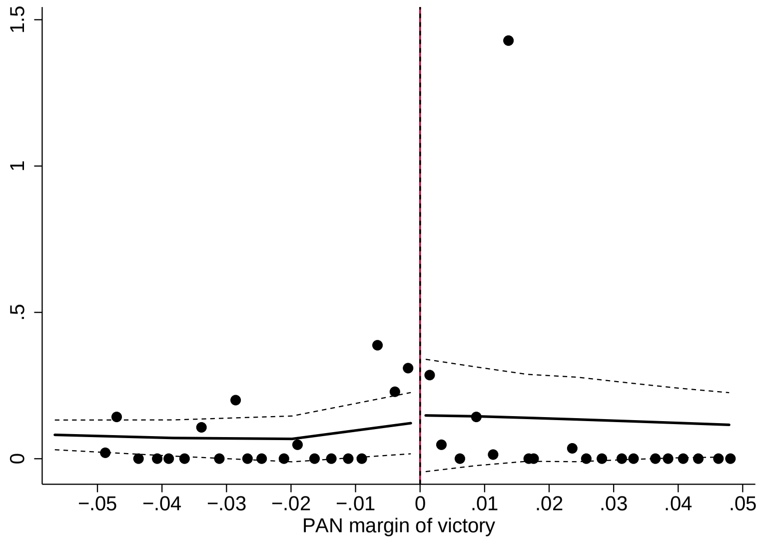
Notes: The left column describes the variation in the policy algorithm (as described in the estimation appendix) and the right column gives the percentage increase in total trafficking costs when the respective variant of the algorithm is used to select edges.

Figure A-1: Close Elections

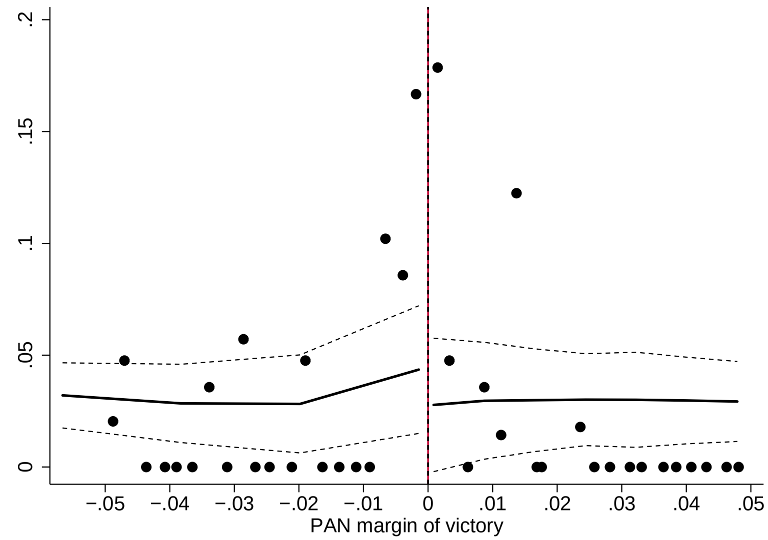


Notes: Black circles denote PAN victories and gray squares denote PAN losses. The sample is limited to municipalities with a vote spread of five percentage points or less.

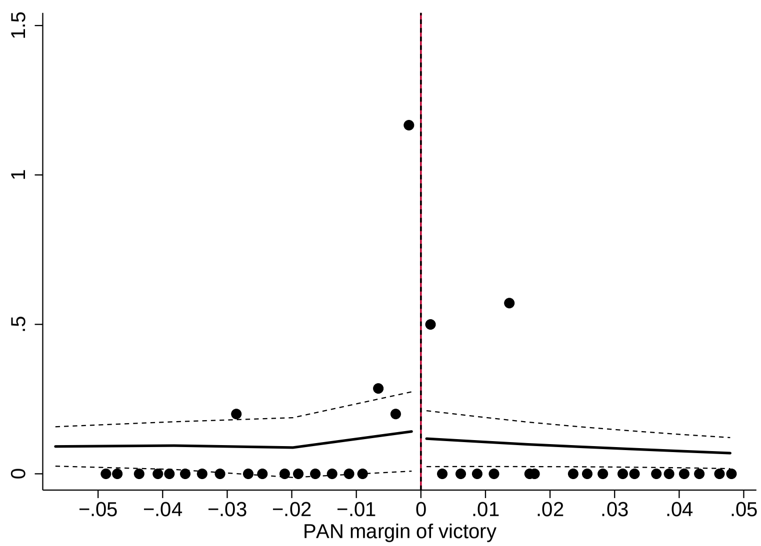
Figure A-2: Covariate Plots



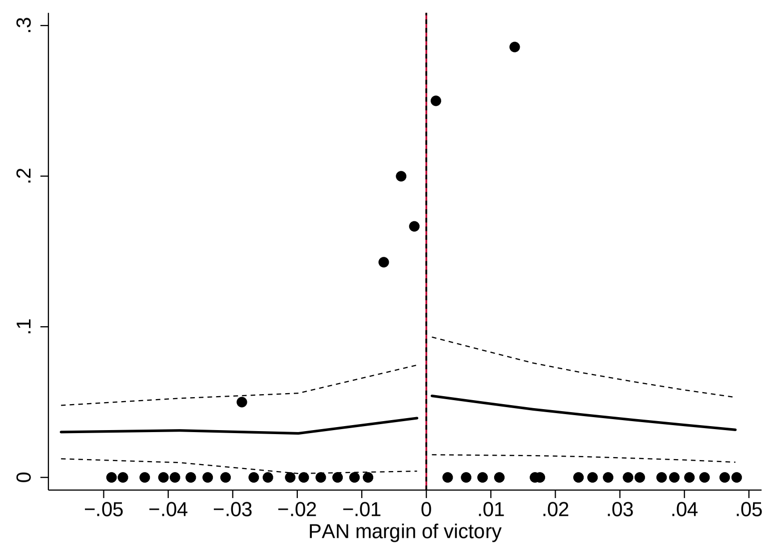
(a) Monthly drug-trade related homicides (Dec. '06 - Jun. '07)



(b) Monthly drug-trade related homicide dummy (Dec. '06 - Jun. '07)

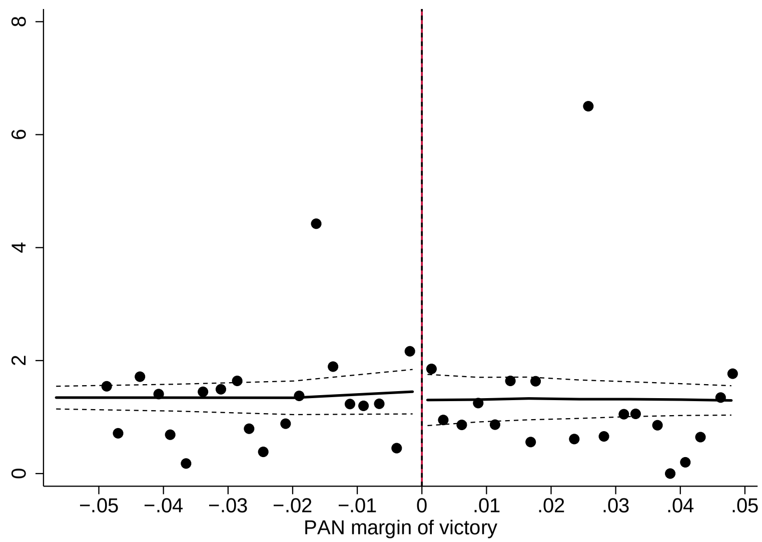


(c) Monthly police-criminal confrontation deaths (Dec. '06 - Jun. '07)

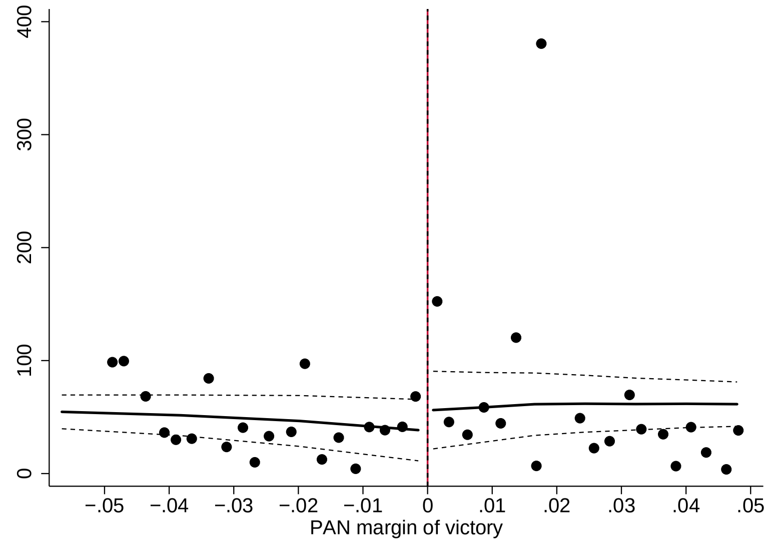


(d) Monthly confrontation deaths dummy (Dec. '06 - Jun. '07)

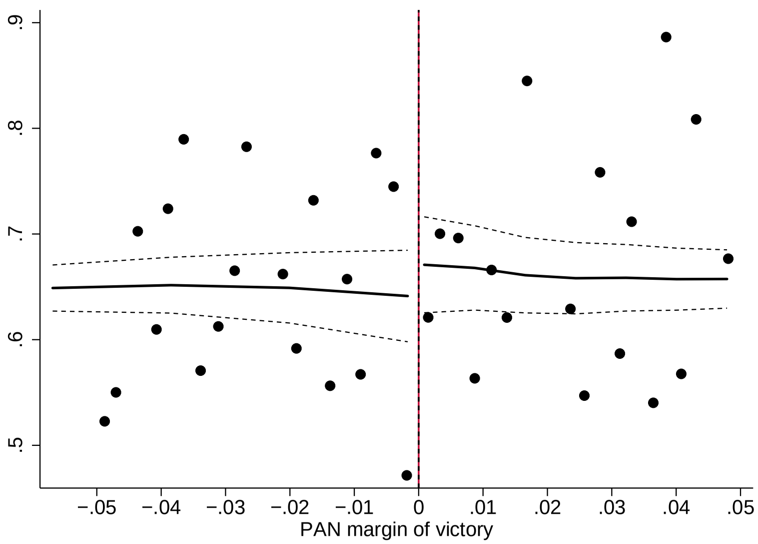
Figure A-3: Covariate Plots



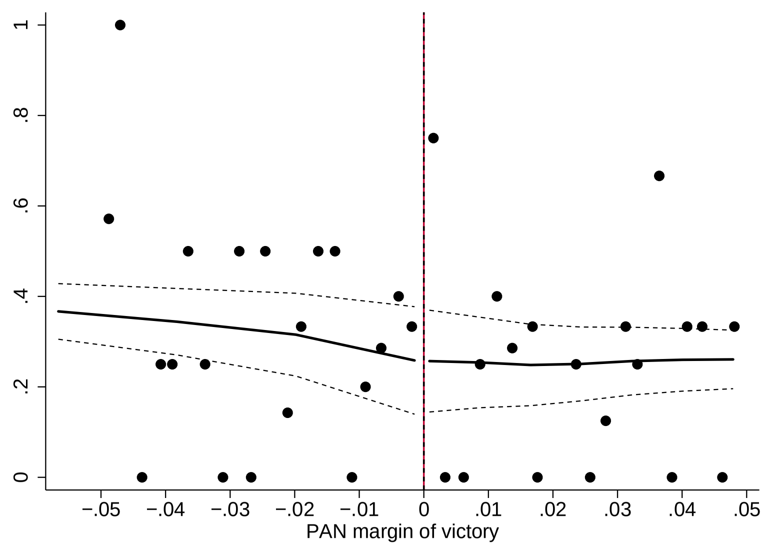
(a) Annual homicide rate per 100,000 inhab. (1990-2006)



(b) Mun. taxes per capita (2005)

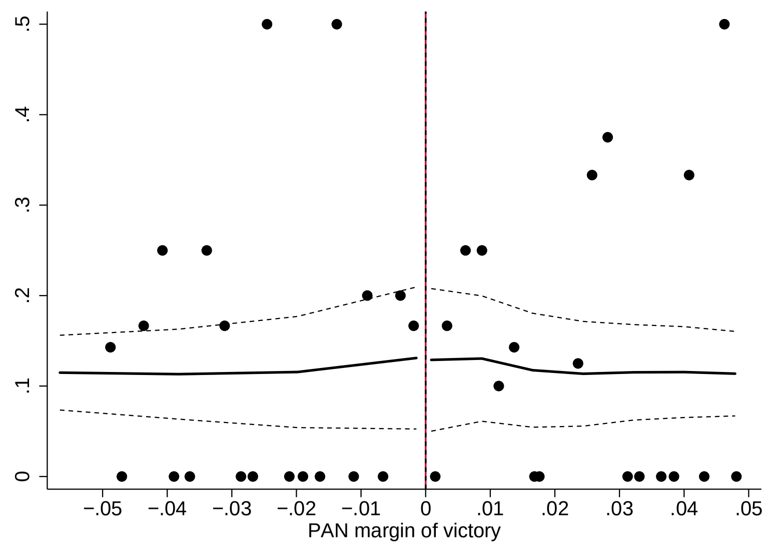


(c) Turnout (2007-2008)

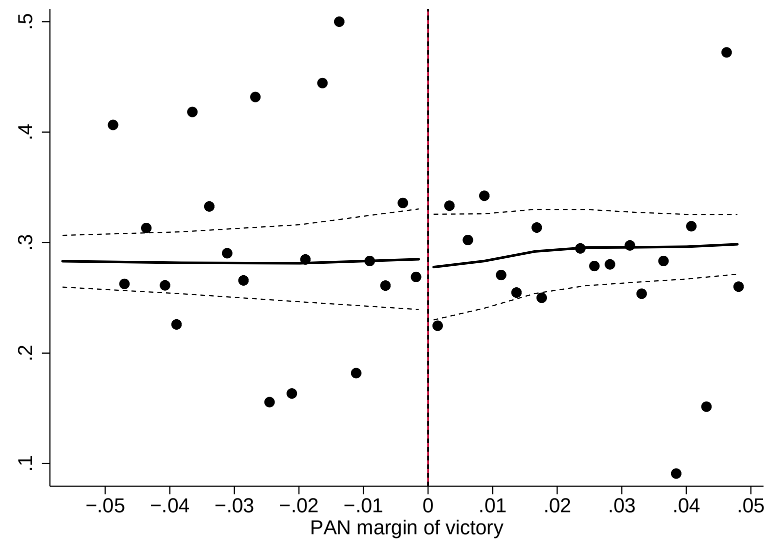


(d) PAN incumbent

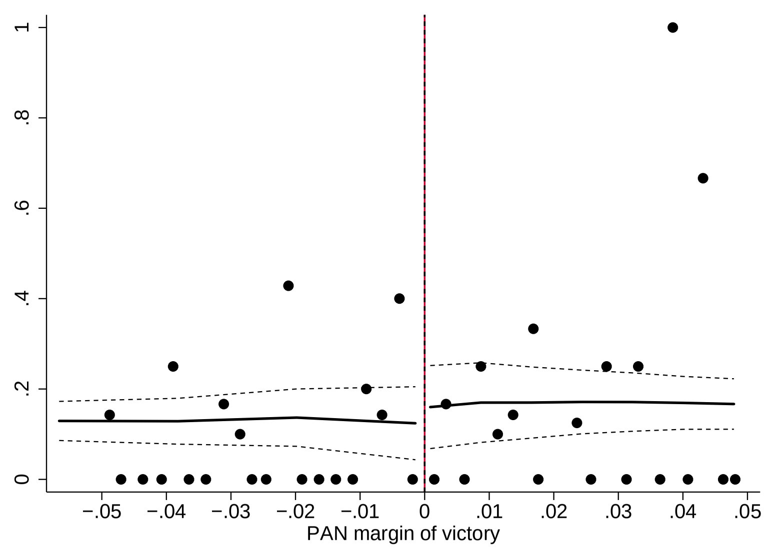
Figure A-4: Covariate Plots



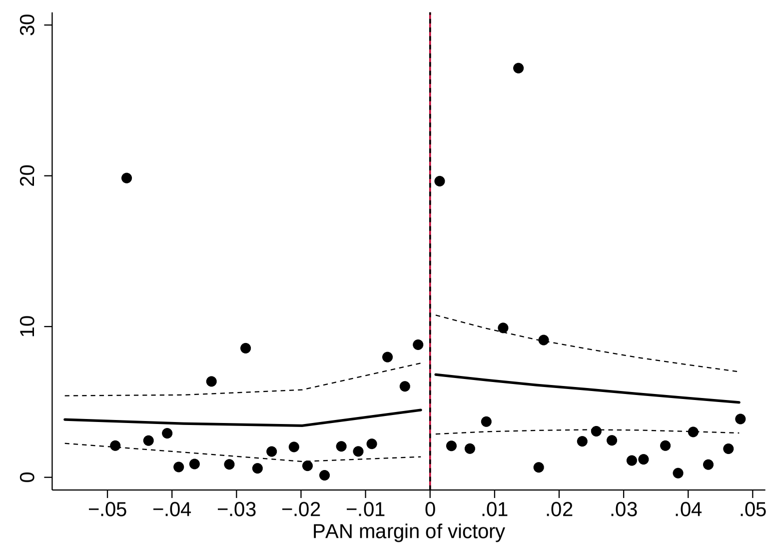
(a) PRD incumbent



(b) % alternations (1976-2006)

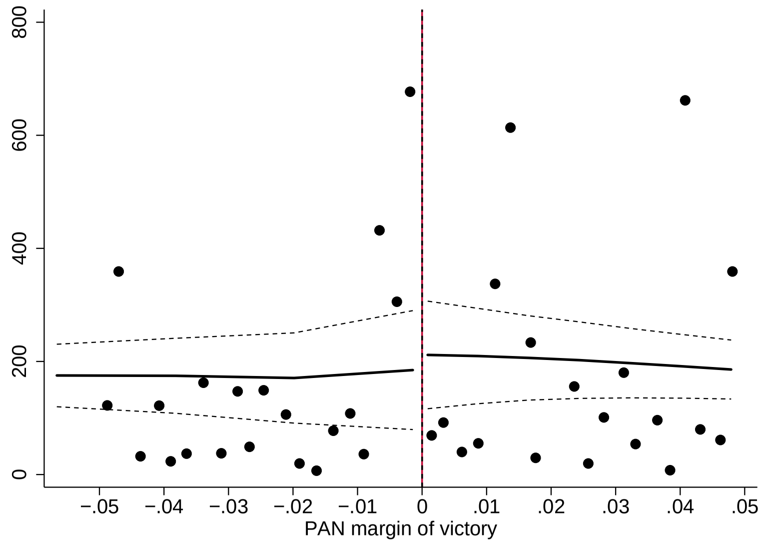


(c) PRI never lost (1976-2006)

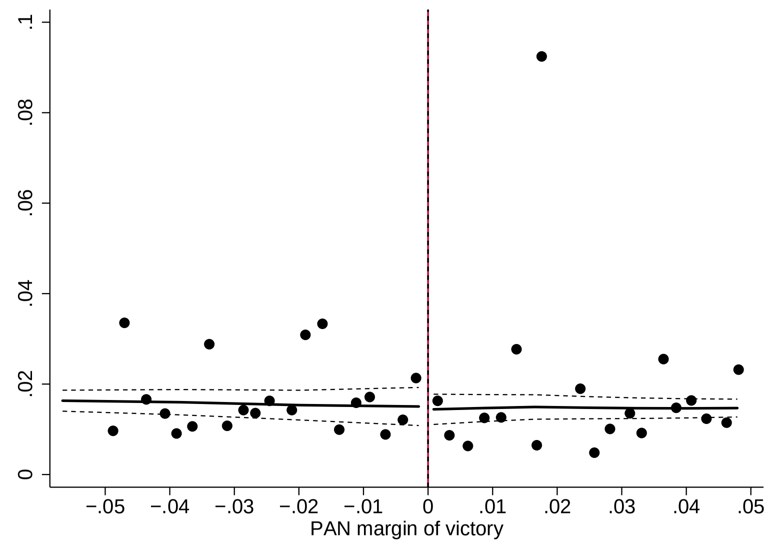


(d) Population (2005)

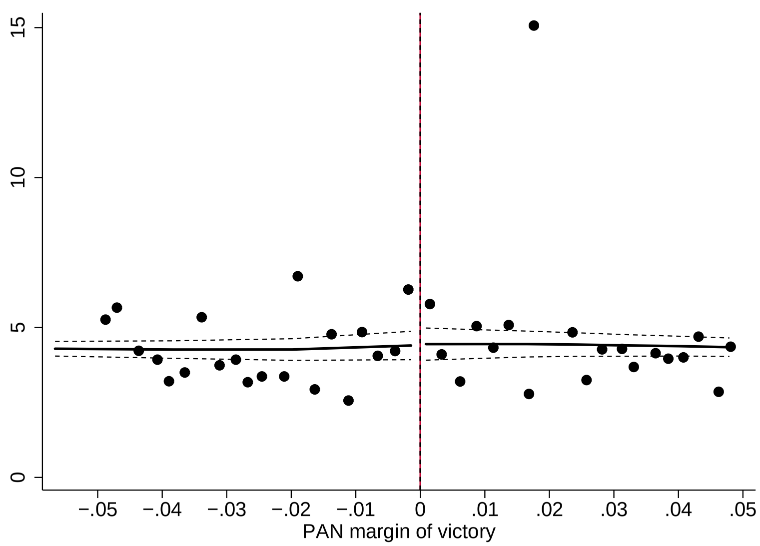
Figure A-5: Covariate Plots



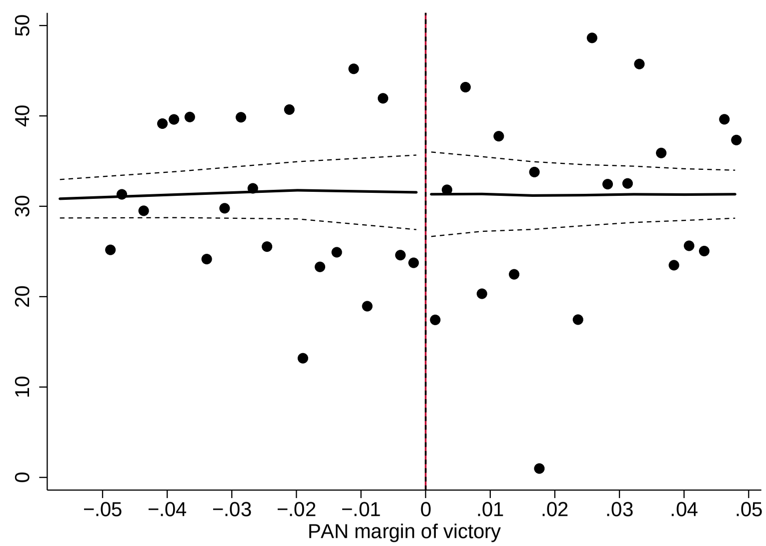
(a) Population density (2005)



(b) Migrants per capita (2005)

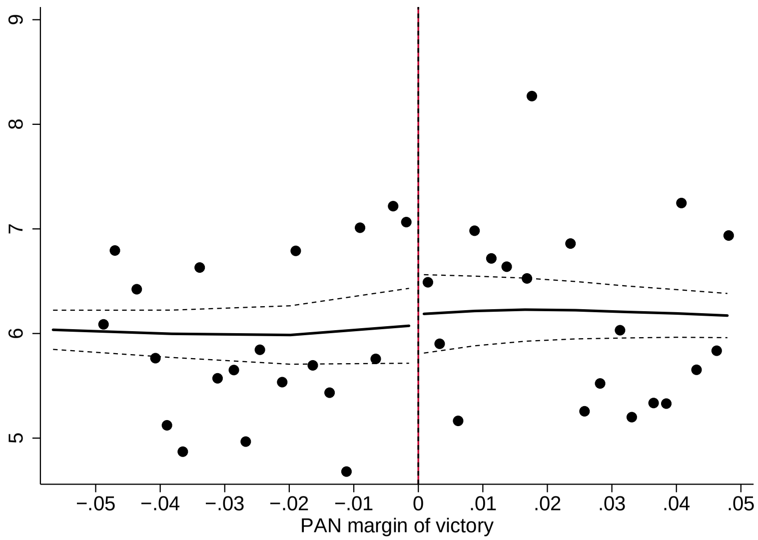


(c) Income per capita (2005)

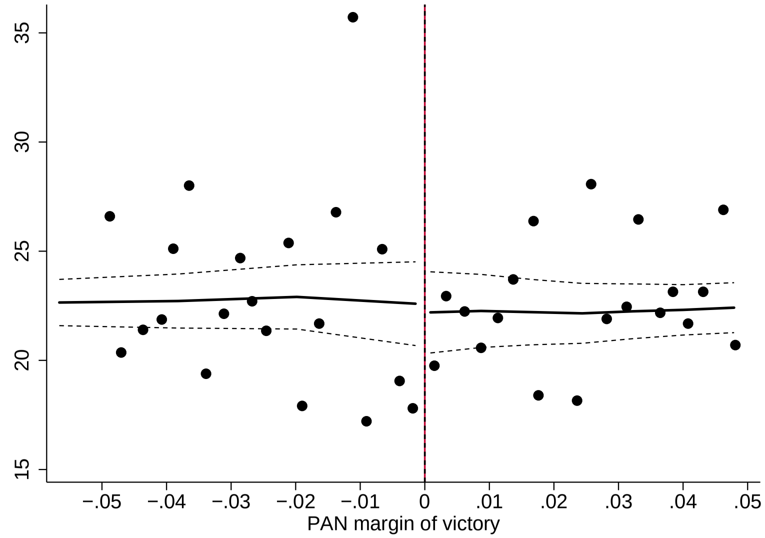


(d) Malnutrition (2005)

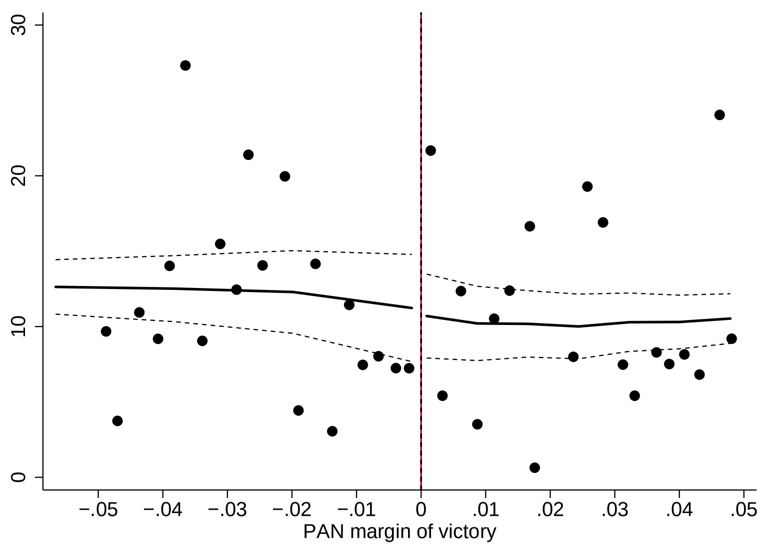
Figure A-6: Covariate Plots



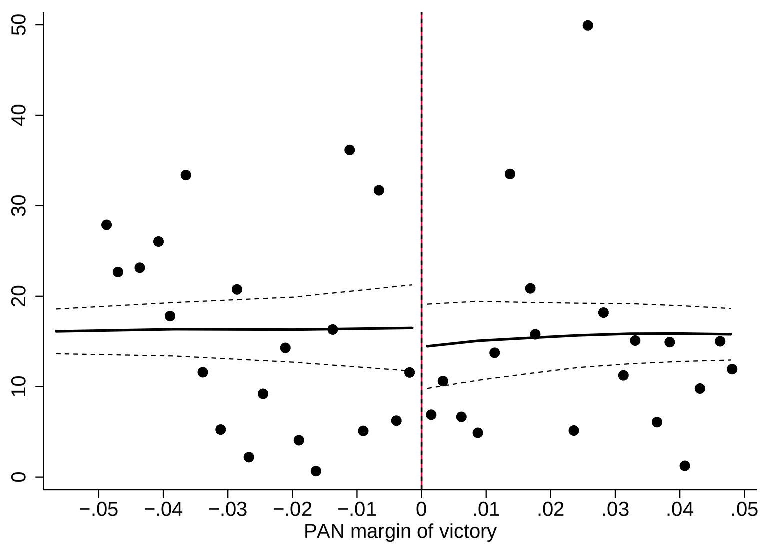
(a) Mean years schooling (2005)



(b) Infant mortality (2005)

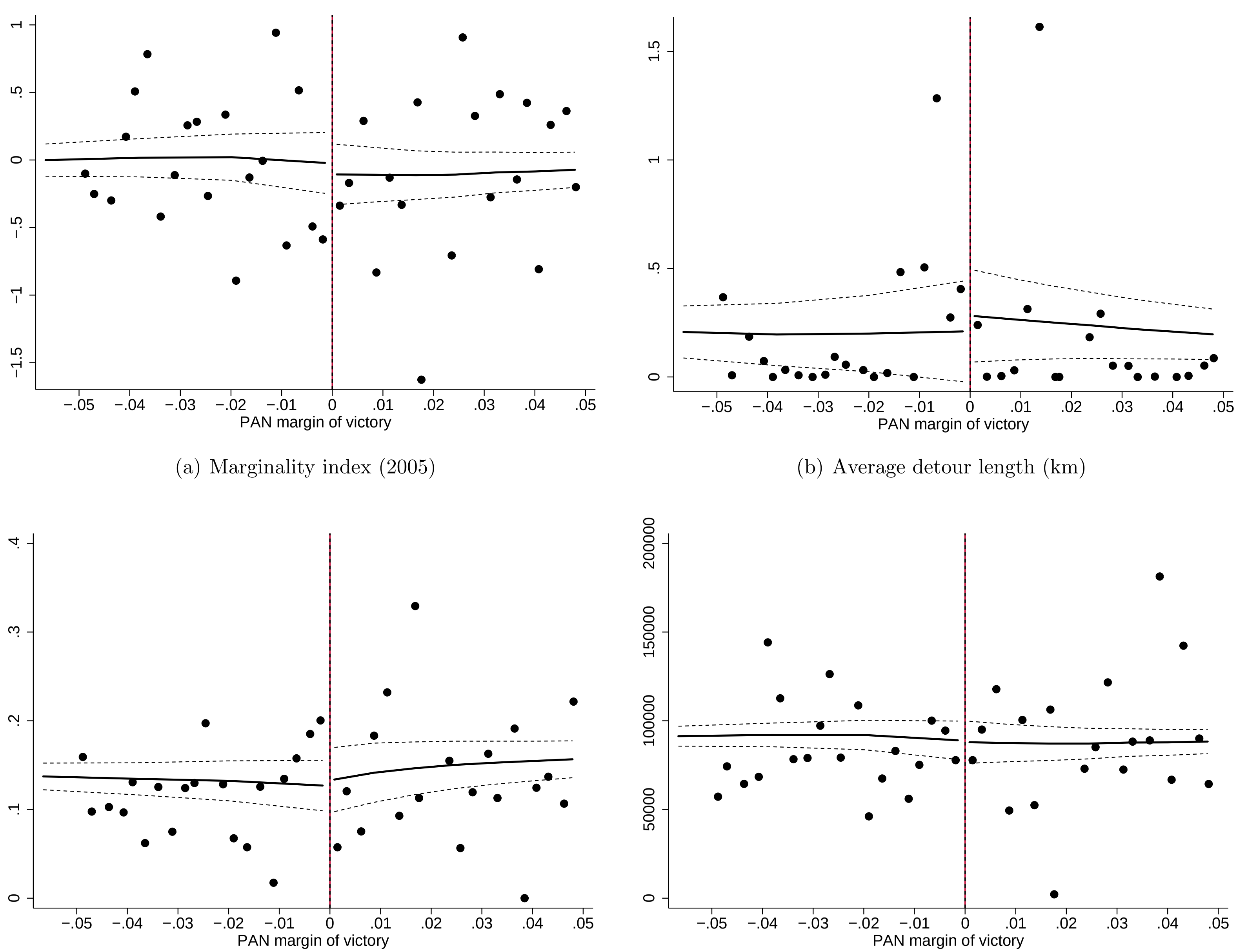


(c) Households w/o access to sewage (2005)



(d) Households w/o access to water (2005)

Figure A-7: Covariate Plots



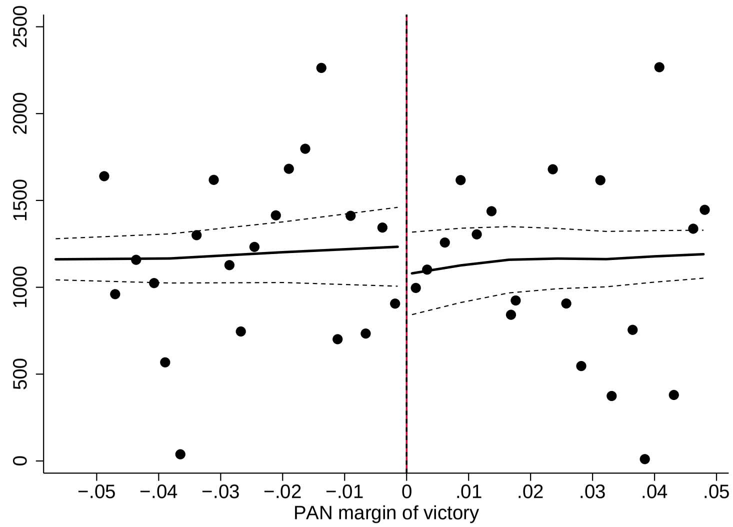
(a) Marginality index (2005)

(b) Average detour length (km)

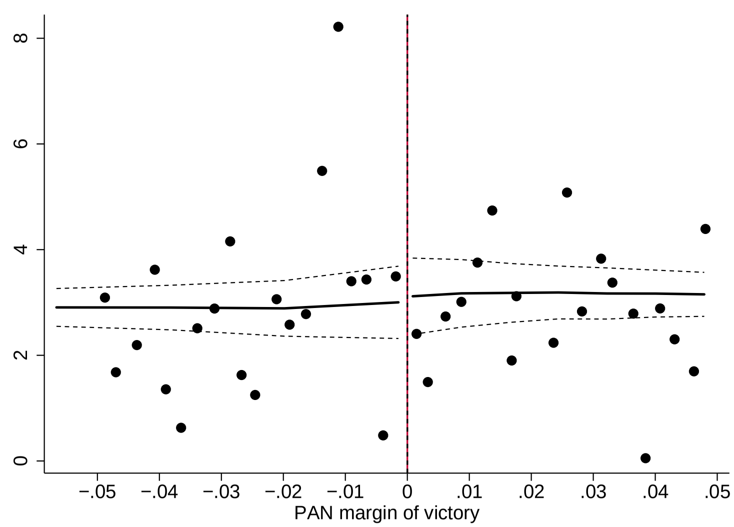
(c) Road density (km/km^2)

(d) Distance U.S. (km)

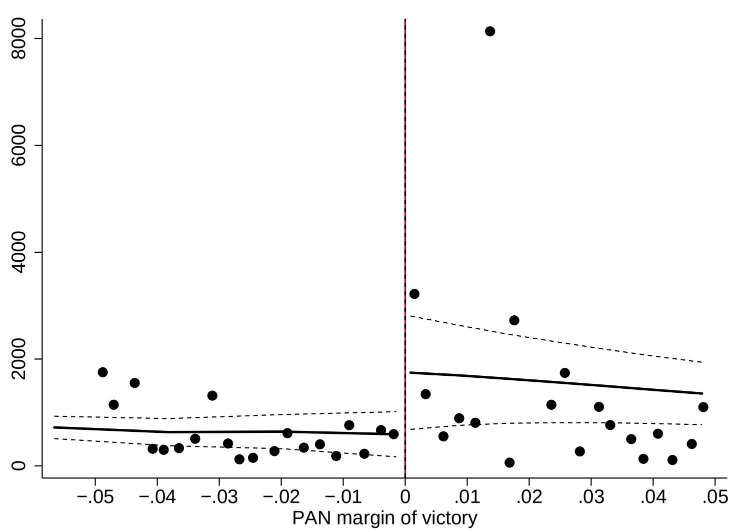
Figure A-8: Covariate Plots



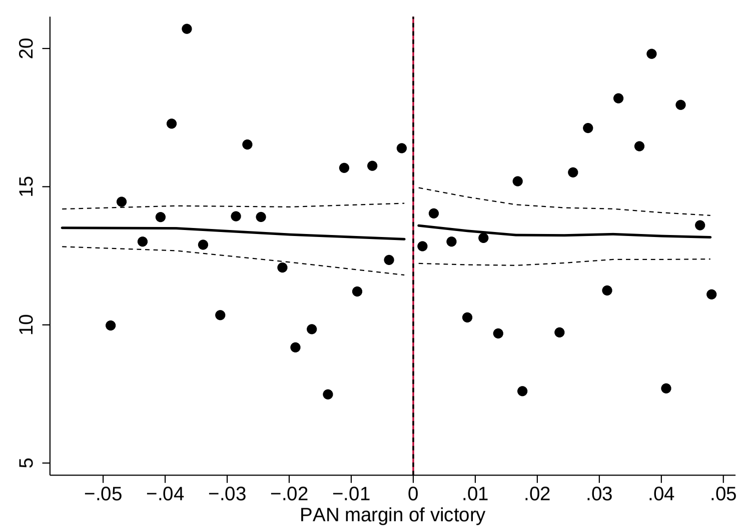
(a) Elevation (m)



(b) Slope (degrees)

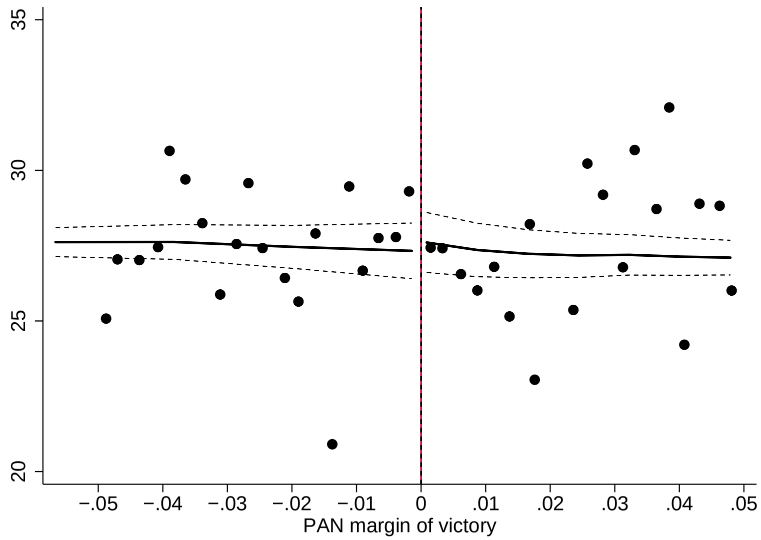


(c) Surface area (km^2)

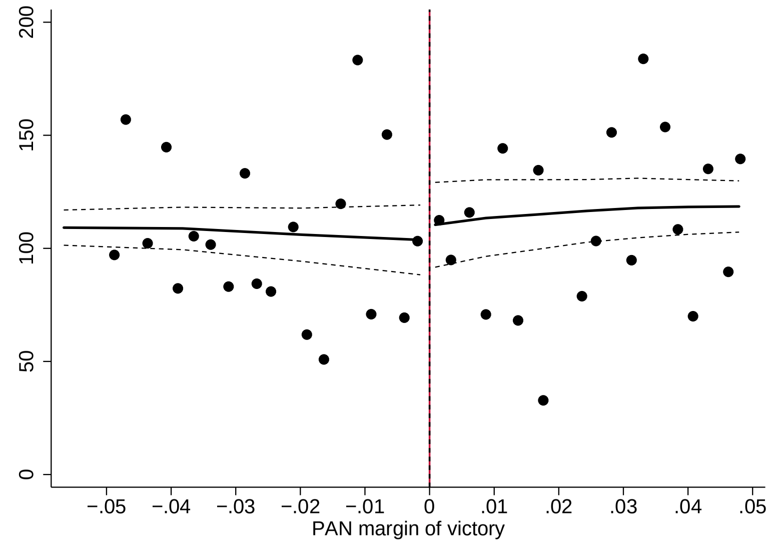


(d) Average min. temperature, C (1950-2000)

Figure A-9: Covariate Plots

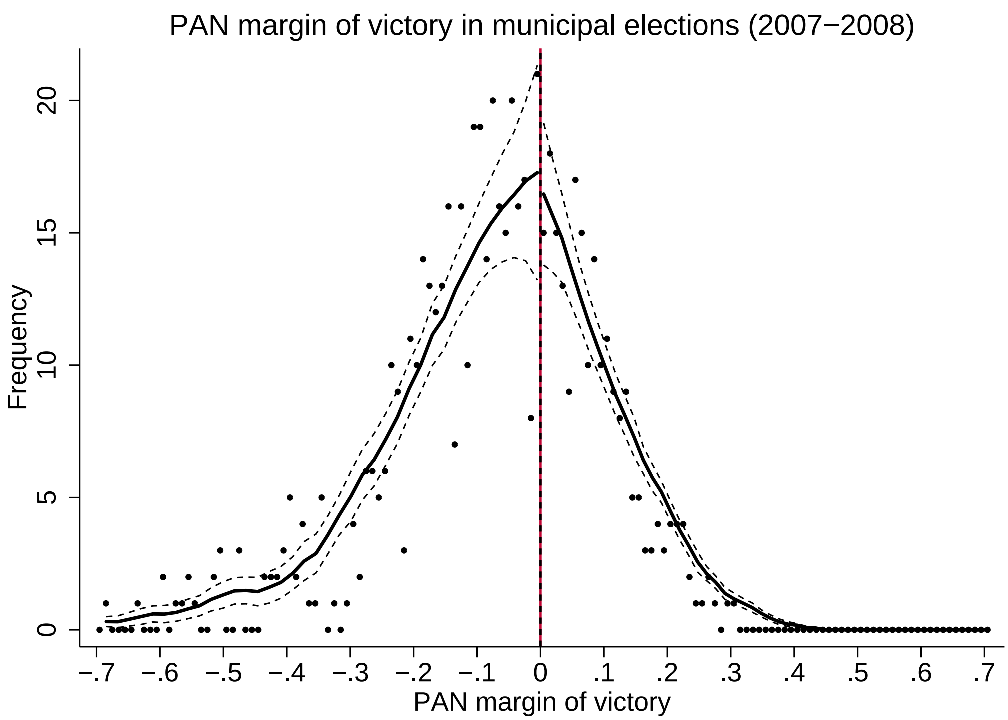


(a) Average max. temperature, C (1950-2000)



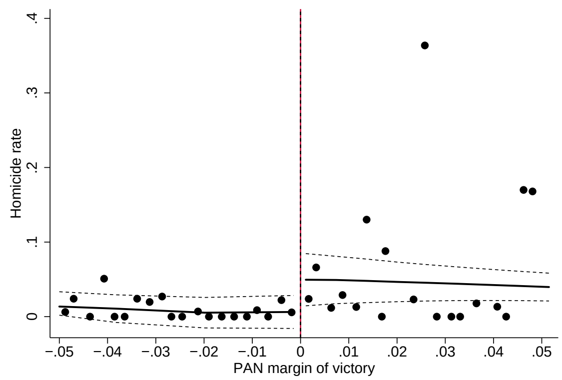
(b) Average precipitation, cm (1950-2000)

Figure A-10: Vote Spread Density

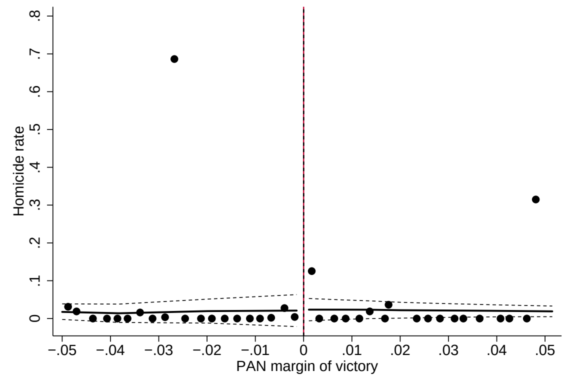


Notes: This figure shows the frequency of mayoral elections (2007-2008) in one percentage point vote spread bins. The solid line plots predicted values from a local linear regression of frequency on vote spread, with separate vote spread trends estimated on either side of the PAN win-loss threshold.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

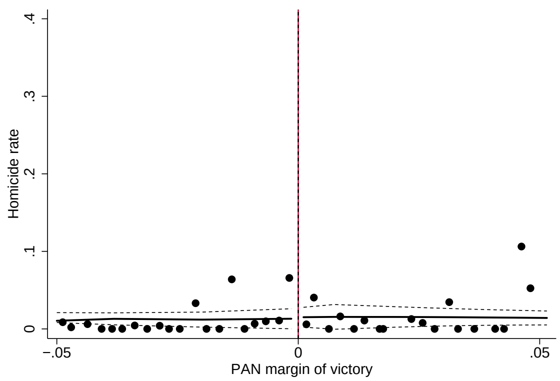
Figure A-11: Drug-trade homicide rate plots



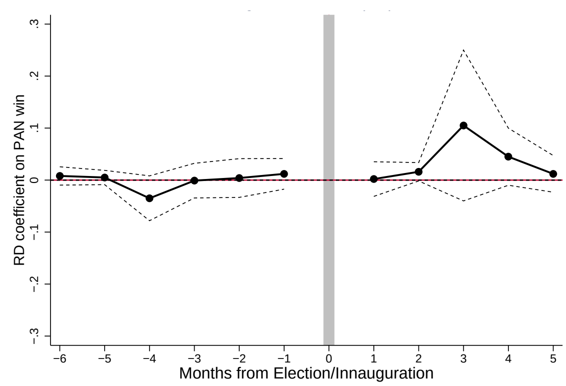
(a) Post-inauguration



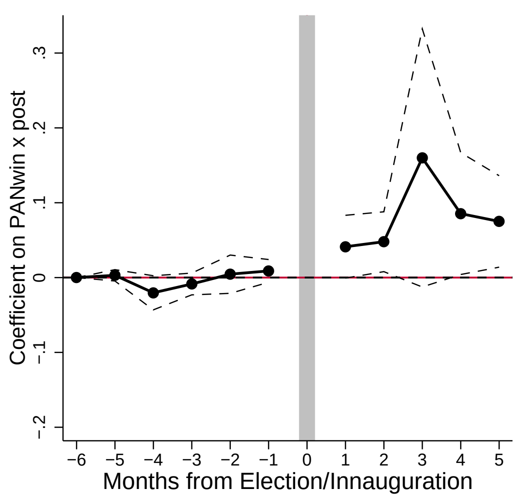
(b) Lame duck



(c) Pre-election

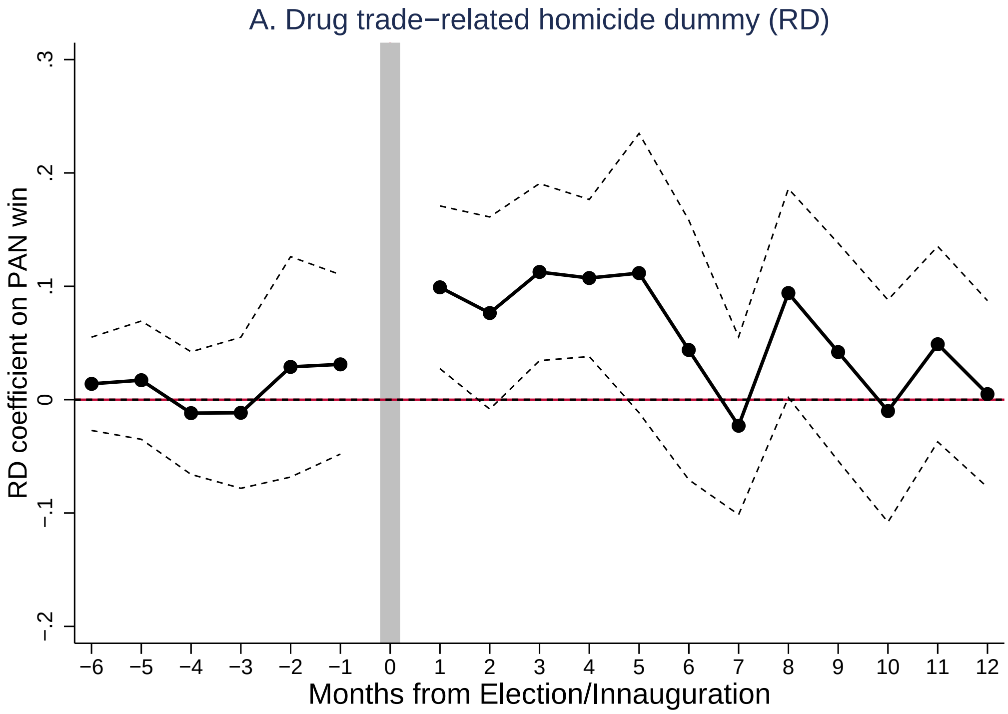


(d) Month-by-month RD



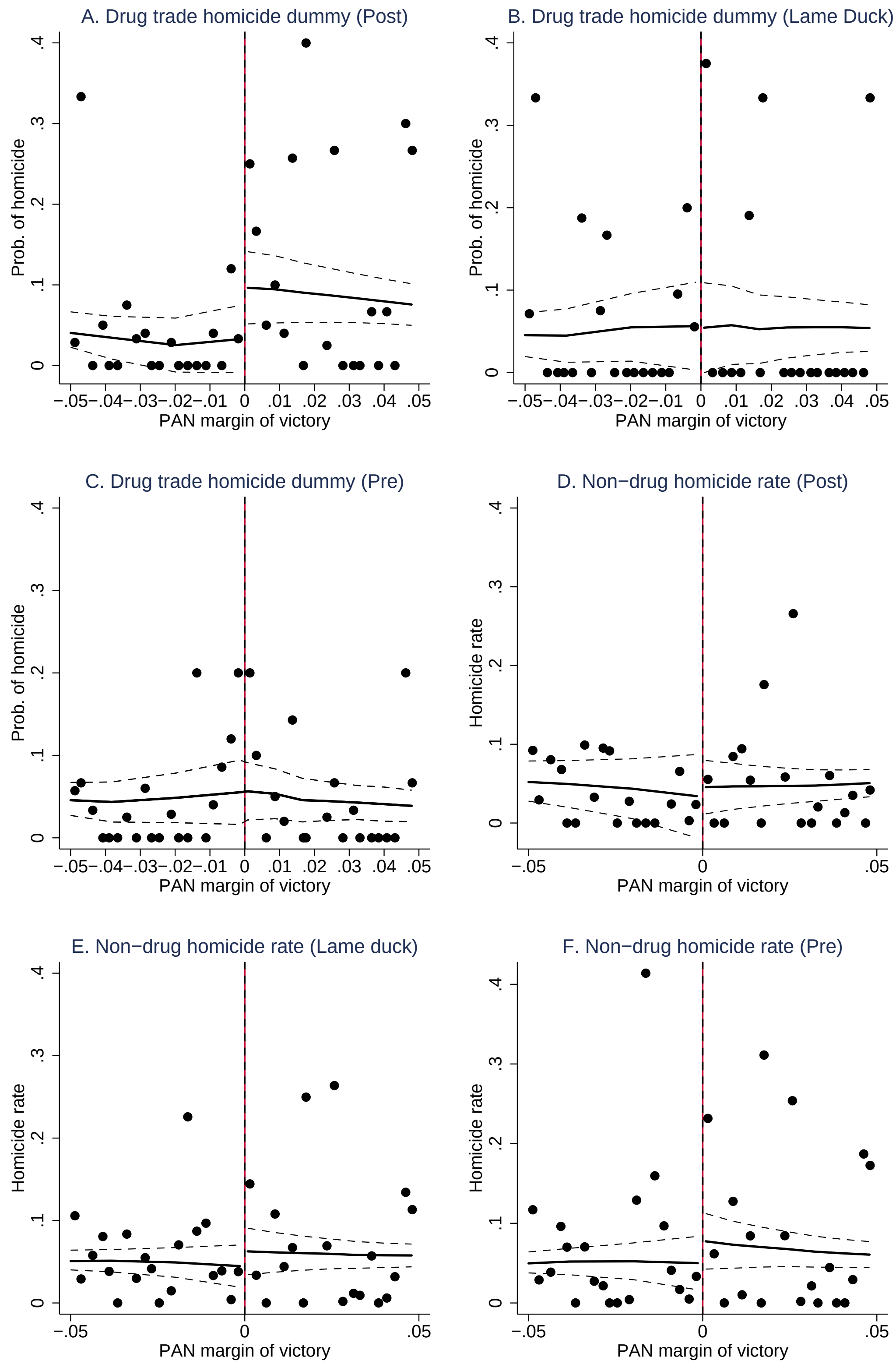
(e) Difference-in-differences

Figure A-12: Close Elections and Violence



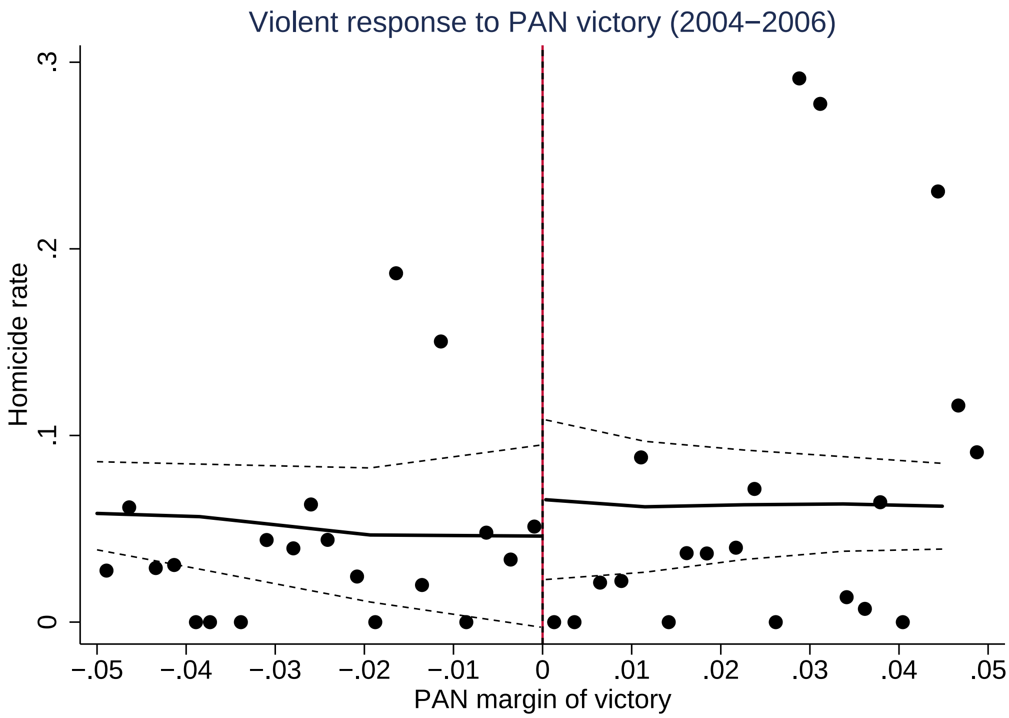
Notes: This figure plots the RD coefficients on PAN win from equation (2) in the main text, estimated separately for each month prior to the election and following the inauguration of new authorities. The dashed lines plot 95% confidence intervals.

Figure A-13: Close PAN Victories and Violence (Larger Sample)



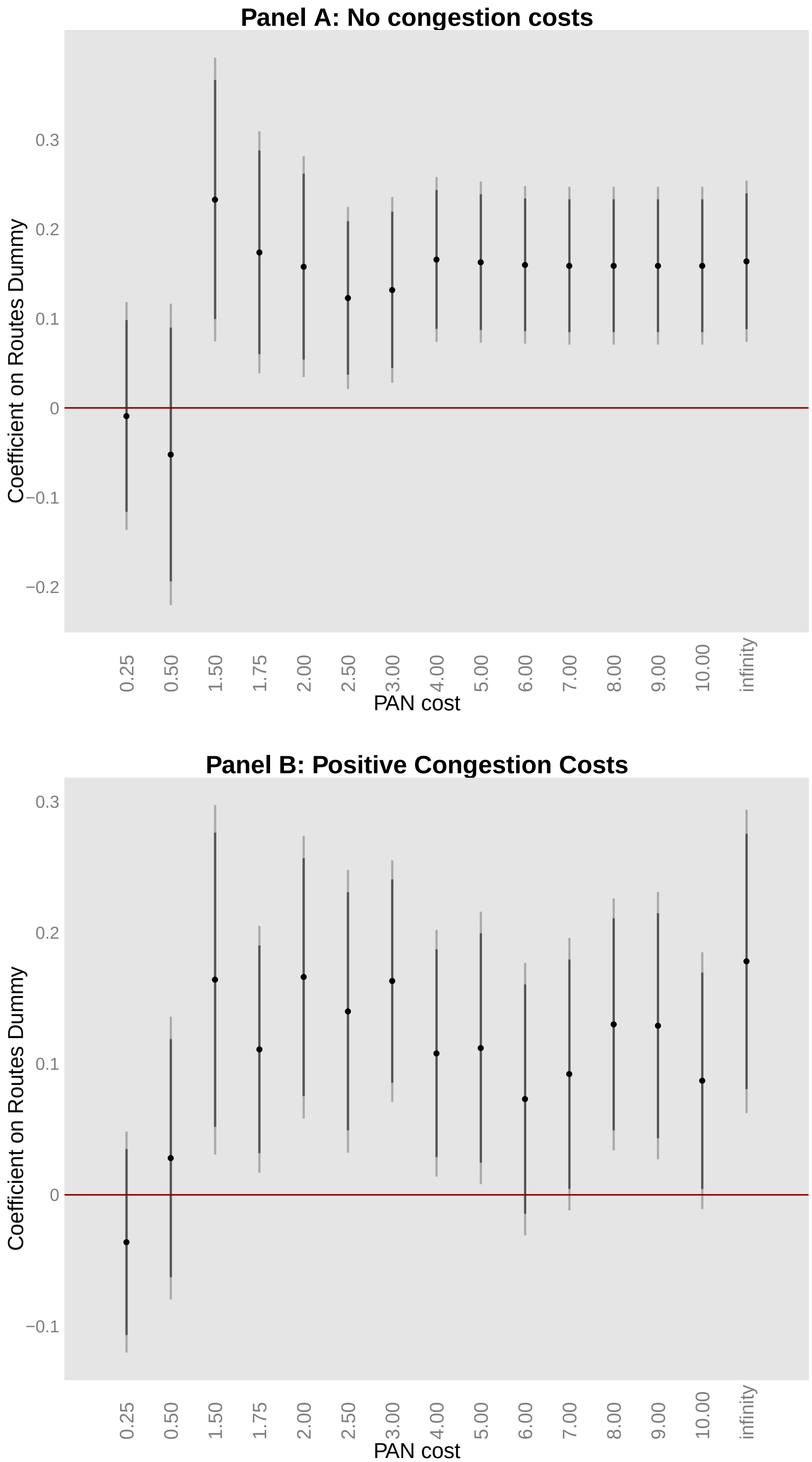
Notes: This figure plots violence measures against the PAN margin of victory, with a negative margin indicating a PAN loss. Each point represents the average value of the outcome in vote spread bins of width 0.0025. The solid line plots predicted values from a local linear regression, with separate vote 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 A-14: Violent Response to PAN Victory (2004-2006)



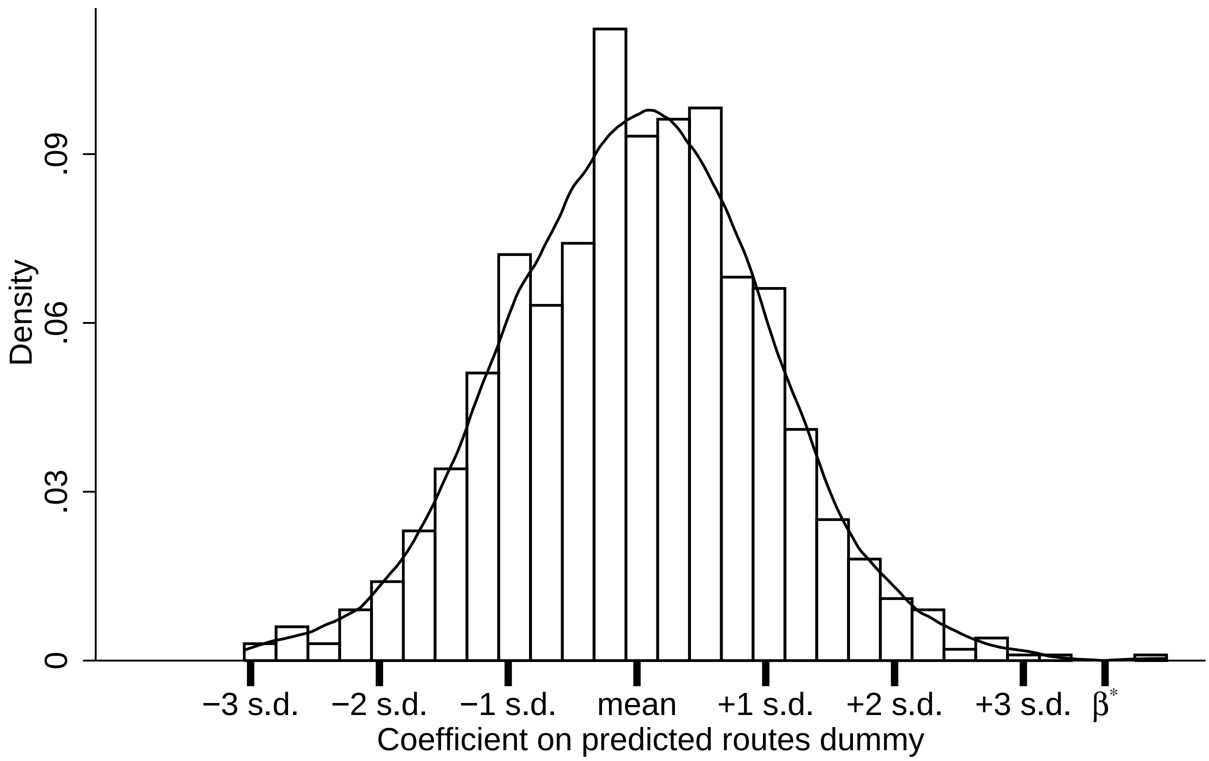
Notes: This figure plots the homicide rate against the PAN margin of victory, with a negative margin indicating a PAN loss. Each point represents the average value of the outcome in vote spread bins of width 0.0025. The solid line plots predicted values from a local linear regression, with separate vote 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 A-15: Varying the Costs Imposed by PAN Victories



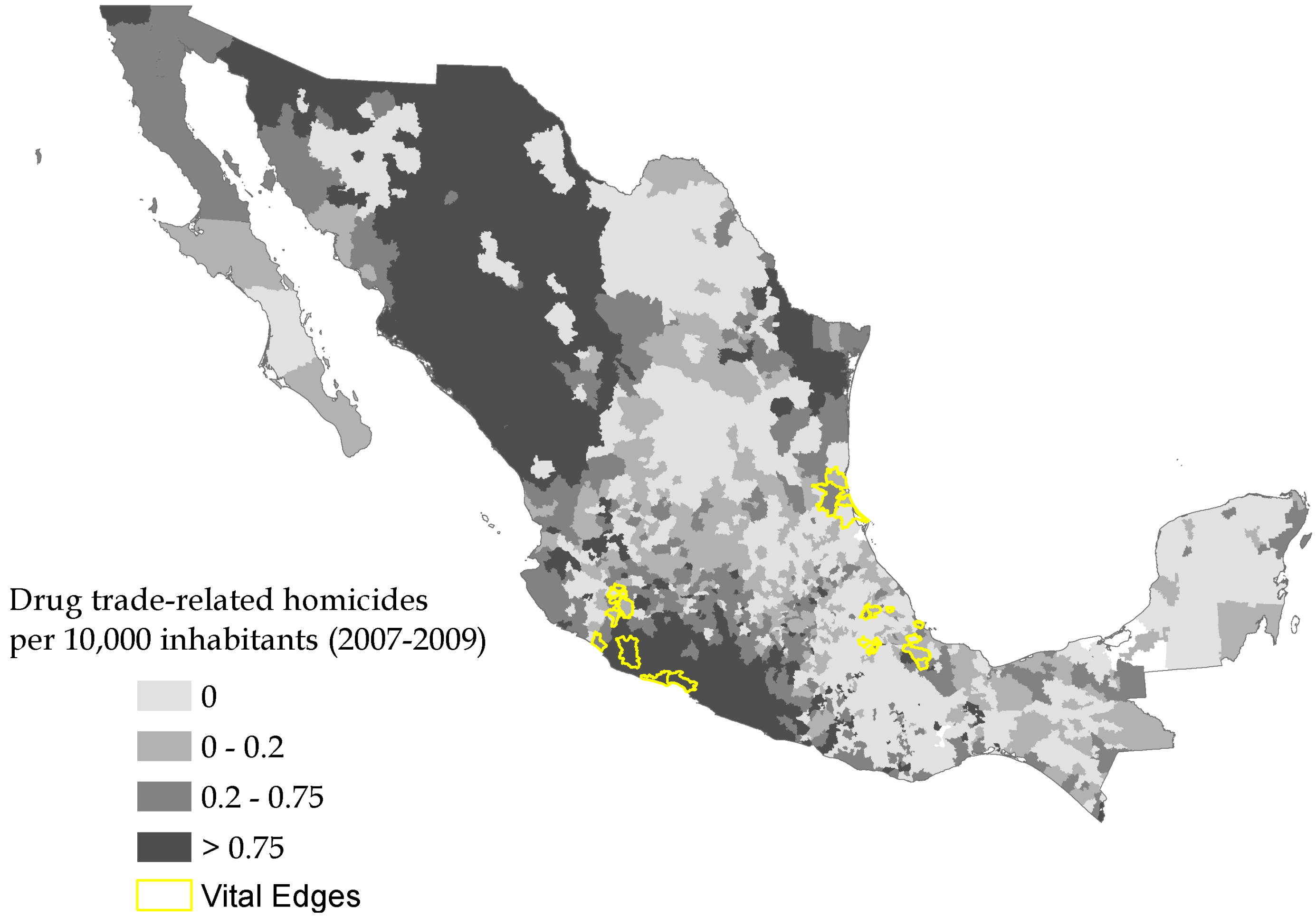
Notes: The y-axis plots the coefficient on the routes dummy in equation (3) when a close PAN victory is assumed to proportionately increase the effective length of edges in the municipality by a factor of α. The x-axis plots values of α ranging from 0.25 to 10. 95% confidence bands are shown with a thin black line and 90% confidence bands with a slightly thicker black line.

Figure A-16: Placebo Exercise



Notes: This figure plots the distribution of coefficients from the placebo exercise described in the text. β^* is the baseline coefficient from Table 5, column (2). The mean of the distribution equals -0.005.

Figure A-17: Law Enforcement Allocation



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