Supplementary Appendix:

Criminal Fragmentation in Mexico

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Contents

A Additional Information

A.1 *Narcoblog* Coding

Narcoblog coding took place in two stages. First, each post in *Borderland Beat* was hand-coded for information about any criminal groups mentioned by name. This definition allows me to track groups over time and offers a way to operationalize some degree of independence, given that even the cells of larger organizations play important roles in conflict. Notably it does not include local members of a broader structure, such as *plaza* leaders. While imperfect, this represented the most transparent, flexible way of defining criminal groups in practice. Posts were additionally coded for any information related to where these criminal actors operated.[1] Groups were coded as present in a location if the *narcoblog* mentions that their territory extends to the region; the group conducted criminal activity there; the group suffered violence there; the group used the municipality as a trafficking route; the group posted or was the subject of propaganda in that area; or an operative of the group was arrested there.

The second step involved using press sources to a) de-duplicate, to combine any groups that operated under multiple names; and b) code additional information about the group's relationship to other organizations. De-duplication is required because some groups adopt different names over time, or may be referred to in multiple different ways. For example, the H2 cartel is also called *Los Patron Sánchez*.

Coding additional information about the group's relationship to other organizations is, of course, dependent on the availability of press coverage about internal cartel dynamics. I broadly split organizations into four categories: major groups, splinters, cells, and unaffiliated groups. I follow recent literature by defining major cartels as the Sinaloa Cartel, Juarez

[1] This included defined regions, such as Michoacán's Tierra Caliente, made up of fewer than 15 municipalities. These were then translated into municipalities.

Cartel, Tijuana Cartel, Gulf Cartel, Zetas, *La Familia Michoacana*, Knights Templar, New Generation Jalisco Cartel, and Beltran Leyva Organization (Sobrino 2020).[2] Some of these groups – notably the *Caballeros Templarios* and Zetas – emerged as splinters themselves; however, they represent the most powerful groups in the country, and the most involved in the international drug trade.

In my coding, splinters are groups whose leadership once belonged to a larger organization, but that no longer answer to the central hierarchy. In press reports, they are often referred to as "splinters," "offshoots," or "breakaway factions." The defining feature of a splinter, as compared to a cell, is whether they continued to draw resources from a bigger group.

By contrast, cells are organizations that operate on behalf of, and draw resources from, a larger organization. In the press, cells are often referred to as "cells," "enforcer groups," or "factions." I do not include temporary or location-specific alliances between groups, which often arise in response to a shared threat. Instead, cells represent more formalized hierarchical relationships. I differentiate between cells and alliances based on (1) whether the group is described as a cell in press reports, (2) the duration and origins of the relationship (whether in response to a temporary threat or more permanent), and (3) whether one group begins as smaller and less powerful, nesting within a larger organization. As a note, eight groups are umbrellas, representing a formalized alliance, typically to fight against a common enemy. For example, the United Cartels, a coalition of groups like the Viagras and the Cartel de Tepalcatepec, fights the CJNG in Michoacán. Since individual group affiliations are often not mentioned, I treat umbrellas as a single cell. While imprecise, I show that results hold dropping umbrella organizations in Appendix B.

Unaffiliated groups are those where no firm relationships, past or present, can be identified in broader press searches. Importantly, this is a category of exclusion. Thus it may capture groups where we lack press coverage about relationships. That said, small groups

[2] I do not include the Valencia Cartel, as it collapsed prior to 2009.

often announce their connections to bigger cartels, given that it affords prestige and protection. Others are mentioned in the press as specifically local groups that an expanding cartel seeks to eliminate.

In practice, differentiating between types of small groups is challenging. Cells may become splinters, and independent groups may be incorporated into cartels as cells. Shifting relationships are difficult to capture quantitatively, since smaller groups are unlikely to have their internal dynamics reported in the press. One limitation of my data is that I treat these relationships as fixed: I do not attempt to document when various changes to a group occur. I use the (assumed) most recent state for each group as its category. A cell that splintered off will be treated as a splinter; an unaffiliated group that became a cell will be coded as a cell. These categories are imperfect, of course. I thus show results using alternatives in Appendix B.

This research does not cover the entire complexity of Mexico's criminal landscape. Notably it does not aim to quantify relationships between state actors and criminal groups (Barnes 2017; Snyder and Durán Martínez 2009; Yashar 2018). Nor does it address self-defense groups, vigilante anti-cartel organizations that often become involved in organized crime themselves. While any self-defense groups known to engage in criminal enterprise I list as a type of criminal group, I identified another 38 *autodefensas* with unclear or no apparent ties to organized crime. I do not include these in the data, since they are conceptually distinct. Empirically, moreover, *autodefensas* often operate as loose networks without a unique name, which makes the likelihood of underreporting their presence much higher.

A.2 *Borderland Beat* Sourcing

I chose *Borderland Beat* as the longest-running and most consistently active blog currently available. It also advertises itself as particularly careful about its sourcing, boasting on its front page that it is "The Most Extensive and Reliable Source of Information Related to the Mexican Drug Cartels." Under the leadership of an editor known as "Buggs" (later revealed to be a retired Albuquerque police officer), *Borderland Beat* relies on a network of contributors located across Mexico and the United States. Information comes from a variety of sources: re-posts and translations of relevant articles from the U.S. or Mexican press; research on a particular topic using open-source materials; re-posts of content from other *narcoblogs*; information discussed on the blog's public forums; and citizen reports, submitted to the blog or found on social media.

To explore sourcing more robustly, I selected a random sample of 100 posts. I then coded two pieces of information. First, I code whether the event or information could be validated using mainstream press (i.e., not *narcoblog* or social media sources). This helps ensure that the blog is not just posting low-quality information that cannot be verified elsewhere. Second, I code the type of information sources used: whether a direct repost from the press; an investigation using press sources; or citizen-submitted reports.

Overall, results provide greater confidence in the quality of information from *Borderland Beat*. Of the 100 links, I failed to validate two in the mainstream press. One was an interview by a contributor with an alleged cartel member; the other analyzed a *narcomanta* and photos of corpses. This suggests that *Borderland Beat* is particularly useful for gleaning relevant information from the press and posting it in one place, with the addition of certain pieces of cartel propaganda – such as *narcomantas* – that may not appear elsewhere.

Aligning with this interpretation, the large majority of the articles relied on press sources. 54 reports were direct reposts of articles from U.S., local, or national news sources. 44 include reporting sourced from the mainstream press. Most of these were research into a particular topic, like the turf war between the CJNG and the Santa Rosa de Lima Cartel. 24 of these additionally incorporated some form of citizen reporting, including photos and videos from social media or user submissions (though the precise origin is often unclear). Two reports relied on unverified, citizen-provided information alone.

A.3 Other Datasets

These data contribute to research on mapping Mexico's criminal organizations. Given that we lack "ground truth" on the presence of criminal groups, the development of multiple data sources allow researchers to triangulate across different methods and sources. Machine learning-based datasets have applied text analysis to track major cartels (Sobrino 2020; Coscia and Rios 2012) or to both identify and track groups (Osorio and Beltran 2020). The latter additionally has the benefit of reporting at an event-level, a granularity not achieved in my data. These datasets draw on expansive news corpuses, and can be run effectively continuously, allowing researchers to maintain up-to-date information. The challenge of identifying group names may still lead to some undercounting: the *narcoblog* data captures almost three times the number of groups in half the timespan of Osorio and Beltran (2020).

Other sources use hand-coded press information. Data from the *Programa de Política de Drogas* more closely matches the groups identified in the *narcoblog* data, though it covers only 2020 and is at the state (rather than municipality) level (BACRIM 2022). The Lantia Intelligence Group maintains information about criminal organizations in Mexico, but does not make the data publicly available (Lantia Intelligence 2022).

Sources based on press reporting all share certain likely biases. In particular, the press is more likely to report on criminal group presence when the group engages in violence or publicly competes for territory, meaning that they may miss groups that are covertly trafficking through certain areas (Anders 2020). To overcome this, some other data sources use intelligence leaks from the Mexican security services. The CIDE-PPE data is based on leaked information covering 2007 to 2011. Newspaper *El Universal* more recently used the Guacamaya leaks – the product of "hacktivism" – to track criminal presence (Aguilar et al. 2024). Military intelligence also has its limits, of course: it will be based on the strength of the intelligence for a particular region, and will be temporally limited by when such leaks occur.

A.4 Validation

Given that there is no agreed-upon ground truth against which to compare my dataset, I approach validation in several ways. First, groups may be systematically overcounted by *Borderland Beat* because of the relatively lower standards to publish – leading to uncorroborated reports of criminal organizations. In part, the blog's sourcing assuages these concerns: it mostly operates as a press aggregator, meaning it is reusing vetted information. While it is infeasible to replicate my coding process with press reports more broadly, I do validate group presence for one municipality for several years in both the local press and the broader mainstream press. In particular, I choose Acapulco, a port city in Guerrero with high levels of tourism and growing rates of criminal violence. I validate my group coding using structured searches of a local paper based out of Acapulco (*El Sur Acapulco*) and of Google-indexed news sources. I focus on the most recent period of data, 2016 to 2020, to overcome the issue of press content being more likely to be removed over time.

Overall this exercise provides greater confidence in *Borderland Beat* as a data source. For the group-year pairs for Acapulco between 2016 and 2020, *El Sur Acapulco* contains information on 24 of 42 observations. However, structured searches of the press perform better, identifying 38 out of 42 observations. This highlights the limits of relying on a single data source. For example, the group *Los Amarillos* was not mentioned in *El Sur Acapulco* in 2018, but the leader was killed in Acapulco in December of that year – a fact confirmed by other reliable news sources, such as *El Universal*. This may be in part a function of the index or searchability of the archives, but nevertheless highlights the role that blogs can play in collating information.

Among the missing cases in broader press searches, one is backfilled according to the rules of my data: the Sinaloa Cartel was mentioned as operating in 2016 and 2018, but not 2017. Two groups could not be confirmed through press sources other than *narcoblogs*, an issue addressed by robustness checks that drop unverified groups. The remaining data point was for an umbrella organization of different groups active in the area; this is also addressed in robustness checks removing the handful of umbrella groups. In general, this highlights the ability of *narcoblogs* to curate and collect information about the drug war.

My second validation addresses the representativeness of *Borderland Beat* compared to Spanish-language *narcoblogs*. For example, *Borderland* may not be representative of the country as a whole, instead focusing on areas at the U.S.-Mexico border. This is in part tested with the Acapulco validation exercise, but to address this more directly I compare groups identified in *Borderland Beat* and popular Spanish-language *Blog del Narco* for the state of Guerrero in 2018-2019. To do so, I hand-coded all posts from *Blog del Narco* mentioning “Guerrero" or one of the names of its municipalities. There is overall high inter-blog reliability. Both identify exactly 44 unique groups operating at the time, although these lists differ for some smaller organizations. 38 of 44 groups appear in both blogs. Of the six present in *Blog del Narco* but not *Borderland Beat*, two were present in the year before, further reducing concerns. This suggests that *Borderland Beat* is fairly representative of *narcoblogs*.

Next, I compare my data to existing datasets on cartel presence. First, I simply find the correlation coefficient between Osorio and Beltran (2020) and Sobrino (2020) across municipality-years. The correlations are quite high: .46 for Sobrino (focusing on dominant groups) and .44 for Osorio and Beltran (all groups). Second, I extend the Acapulco analysis described above, comparing the groups identified in press sources, the *narcoblog* data, and Osorio and Beltran (2020) and Sobrino (2020). Osorio and Beltran (2020) identify two groups in Acapulco between 2009 and 2017, plus several unidentified organizations; Sobrino (2020) finds all nine dominant cartels operated in Acapulco from 2013 onwards, more than my data identify. Given confirmation from press sources, this suggests that hand-coding still offers some benefits for identifying organizations.

I also compare my data to the content produced by *El Universal* following the Guacamaya leaks, based on military reports. These data are quite incomplete, however, given that they are based on piecing together non-systematic military reports. For example, the Guacamaya data suggest only two groups operated in the state of Guerrero in 2021, and none in previous years. As a result, the correlation between my dataset and the Guacamaya leaks is lower (.1).

A.5 Kingpin Treatment

To define a municipality as "treated" by a kingpin capture, I combine the *narcoblog* data with information on kingpin captures and deaths between 2009 and 2020. I draw on the U.S. Office of Foreign Assets Control (OFAC) Sanctions List, which in Mexico covers the major operators of organizations trafficking drugs into the United States. I count as a kingpin all primary leaders and their high-level lieutenants, excluding financial operators, trafficking coordinators, family members, and local *plaza* heads (the latter because the OFAC list severely undercounts this layer of leadership). I then code these individuals for their date of death or capture. In total, this leaves me with 44 cases of kingpin removals. The main limitation of the data is that it covers organizations operating transnationally, meaning it does not include largely domestic groups – which also means that more kingpins were identified and captured during the early period of the data. Still, the OFAC lists cover the majority of high-profile deaths and arrests. The Center for Advanced Defense Studies generously provided the raw, filtered data.

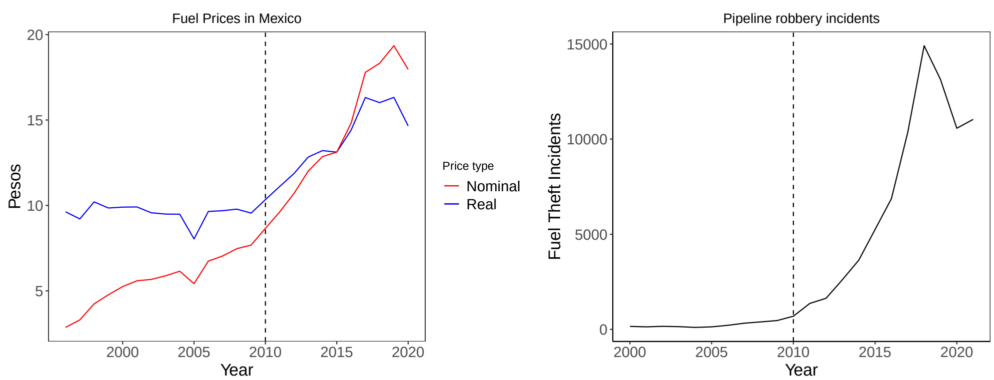
If a targeted group was known to operate in area m in year t or $t-1$, where t is the year of a kingpin capture, then a municipality is considered affected by the kingpin strategy in years t through $t+2$. For example, if the Zetas operated in San Fernando in 2010, and a Zeta leadership arrest occurred in 2011, then San Fernando would be considered "treated" between 2011 and 2013. I focus on just a three-year post-capture window for two reasons. Theoretically, we may expect most effects to occur early, as the renegotiation of territorial control and cartel hierarchy occurs. Practically, most kingpin captures affect large cartels, and the majority of kingpin captures occurred between 2009 and 2015. Because cartels' operational areas are fairly stable – the base Tijuana Cartel is always Tijuana – this leaves many municipalities effectively "always treated," despite the fact that we might expect each kingpin capture to have additive effects. In the main specifications, then, a municipality that has not experienced a kingpin capture for three years is considered pre-treatment. Results are robust to different definitions of "affected" municipalities.

For the event studies, leads and lags take the smallest value from 0 to 2 if there had been a recent kingpin assassination; they are negative only if a municipality had not yet been affected, or more than two years had passed since a prior kingpin removal. All other years are considered pre-treatment.

A.6 Gas Prices and Fuel Theft

The figure below descriptively demonstrates that the rise in annual domestic gas prices correlates with reported fuel theft incidents.

Figure A1: Gas Prices and Fuel Theft Incidents



Left panel: gas prices in 2016 pesos in Mexico. This plot confirms that real gas prices began rising in 2010, after the Mexican government decided to phase out fuel subsidies. Right: fuel thefts annually.

A.7 Full Tables

Results below show tables for the results in the main text, including dropped controls (other than state by year linear time trends).

Table A1: Kingpin Removals and Criminal Groups: Full Tables

	Major (1)	Minor (2)	Emergence (3)	Expansion (4)
Kingpin Removal	0.76***	0.23***	0.09***	0.39***
	(0.02)	(0.03)	(0.01)	(0.02)
PAN party mayor	-0.01	-0.01	-0.02*	0.01
	(0.01)	(0.03)	(0.007)	(0.01)
Marijuana Hectares	-0.03**	-0.15***	0.007	-0.0008
	(0.01)	(0.03)	(0.010)	(0.01)
Poppy Hectares	0.04**	0.01	-0.02	-0.02
	(0.01)	(0.03)	(0.01)	(0.02)
R^2	0.70	0.57	0.30	0.27
Observations	29,480	29,480	29,480	29,480
Dependent variable mean	0.25	0.24	0.06	0.17
municipality fixed effects	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

Table A2: Gas Pipelines and Criminal Groups: Full Tables

	Major (1)	Minor (2)	Emergence (3)	Expansion (4)
Gas Pipeline x Price	0.06**	0.11***	-0.009	0.05***
	(0.02)	(0.03)	(0.01)	(0.02)
PAN party mayor	-0.04*	-0.02	-0.02*	-0.002
	(0.02)	(0.03)	(0.008)	(0.01)
Marijuana Hectares	-0.04***	-0.16***	0.005	-0.009
	(0.01)	(0.03)	(0.010)	(0.01)
Poppy Hectares	0.04**	0.02	-0.02	-0.01
	(0.01)	(0.03)	(0.01)	(0.02)
R^2	0.63	0.57	0.30	0.25
Observations	29,480	29,480	29,480	29,480
Dependent variable mean	0.25	0.24	0.06	0.17
municipality fixed effects	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

A.8 Results by Group Type

In the main body of the paper, I show results only for "major" and "minor" organizations. In this section I further disaggregate results by *type* of minor group – whether splinters, cells, or unaffiliated. Findings show that kingpins are correlated primarily with an increase in splinters and cells, rather than unaffiliated groups, suggesting that the policy mainly relates to the operations of larger cartels.

Table A3: Results by Group Type

	Splinters		Cells		Unaffiliated	
	(1)	(2)	(3)	(4)	(5)	(6)
Kingpin Removal	0.11***		0.12***		-0.001	
	(0.02)		(0.02)		(0.01)	
Gas Pipeline x Price		0.05**		0.02		0.04***
		(0.01)		(0.02)		(0.01)
PAN party mayor	-0.007	-0.01	-0.008	-0.01	0.0004	-0.0002
	(0.01)	(0.01)	(0.02)	(0.02)	(0.005)	(0.005)
Marijuana Hectares	-0.10***	-0.10***	-0.04**	-0.04**	-0.01*	-0.01*
	(0.02)	(0.02)	(0.01)	(0.01)	(0.007)	(0.007)
Poppy Hectares	0.02	0.03+	0.01	0.01	-0.02*	-0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.55	0.55	0.49	0.49	0.30	0.31
Observations	29,480	29,480	29,480	29,480	29,480	29,480
Dependent variable mean	0.11	0.11	0.10	0.10	0.04	0.04
municipality fixed effects	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

Table A4: Results by Group Type (Emergence)

	Splinters		Cells		Unaffiliated	
	(1)	(2)	(3)	(4)	(5)	(6)
Kingpin Removal	0.03***		0.07***		-0.04***	
	(0.004)		(0.009)		(0.010)	
Gas Pipeline x Price		0.002		-0.008		0.01**
		(0.004)		(0.005)		(0.005)
PAN party mayor	-0.0010	-0.002	-0.01*	-0.02**	0.0006	0.002
	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)
Marijuana Hectares	0.004	0.003	0.004	0.003	-0.007	-0.006
	(0.003)	(0.003)	(0.005)	(0.005)	(0.007)	(0.007)
Poppy Hectares	-0.0003	4.1×10^{-5}	0.01**	0.01**	-0.03**	-0.03**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.01)	(0.01)
R^2	0.19	0.19	0.24	0.23	0.24	0.24
Observations	27,024	27,024	27,024	27,024	27,024	27,024
Dependent variable mean	0.02	0.02	0.02	0.02	0.02	0.02
municipality fixed effects	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

Table A5: Results by Group Type (Expansion)

	Splinters		Cells		Unaffiliated	
	(1)	(2)	(3)	(4)	(5)	(6)
Kingpin Removal	0.005		0.03**		0.01**	
	(0.009)		(0.01)		(0.004)	
Gas Pipeline x Price		0.03***		-0.002		0.02***
		(0.009)		(0.006)		(0.005)
PAN party mayor	-0.002	-0.003	-0.002	-0.003	0.0008	0.0002
	(0.008)	(0.008)	(0.006)	(0.006)	(0.002)	(0.002)
Marijuana Hectares	-0.04***	-0.04***	-0.0010	-0.002	-0.002	-0.002
	(0.007)	(0.007)	(0.008)	(0.008)	(0.002)	(0.002)
Poppy Hectares	0.004	0.005	-0.004	-0.004	0.001	0.002
	(0.009)	(0.009)	(0.01)	(0.01)	(0.002)	(0.002)
R^2	0.22	0.22	0.23	0.23	0.12	0.12
Observations	27,024	27,024	27,024	27,024	27,024	27,024
Dependent variable mean	0.04	0.04	0.04	0.04	0.009	0.009
municipality fixed effects	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

A.8.1 Alternate Categories

I choose to track four categories of groups: major cartels, splinters, cells, and unaffiliated groups. A limitation of the data is that I treat these groups as fixed, to avoid the challenge of understanding often opaque internal group processes. I additionally show sub-type results are robust to treating cells instead as any group that was once part of a hierarchy, even if they later splintered. I additionally show that results are robust to differentiating between affiliated and unaffiliated groups only.

Table A6: Kingpin Removals and Fuel Theft, Alternate Cell/Splinter Coding

	Splinters		Cells	
	(1)	(2)	(3)	(4)
Kingpin Removal	0.09***		0.14***	
	(0.02)		(0.02)	
Gas Pipeline x Price		0.04*		0.03
		(0.01)		(0.02)
PAN party mayor	-0.007	-0.01	-0.008	-0.01
	(0.01)	(0.01)	(0.02)	(0.02)
Marijuana Hectares	-0.11***	-0.11***	-0.03*	-0.03**
	(0.02)	(0.02)	(0.01)	(0.01)
Poppy Hectares	0.03+	0.03+	0.009	0.01
	(0.02)	(0.02)	(0.01)	(0.01)
R^2	0.54	0.54	0.50	0.50
Observations	29,480	29,480	29,480	29,480
Dependent variable mean	0.09	0.09	0.11	0.11
municipality fixed effects	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

Table A7: Kingpin Removals and Fuel Theft, Affiliated vs Unaffiliated

	Affiliated		Unaffiliated	
	(1)	(2)	(3)	(4)
Kingpin Removal	0.99***		-0.001	
	(0.04)		(0.01)	
Gas Pipeline x Price		0.12***		0.04***
		(0.04)		(0.01)
PAN party mayor	-0.03	-0.06+	0.0004	-0.0002
	(0.03)	(0.03)	(0.005)	(0.005)
Marijuana Hectares	-0.17***	-0.19***	-0.01*	-0.01*
	(0.03)	(0.03)	(0.007)	(0.007)
Poppy Hectares	0.07*	0.08*	-0.02*	-0.02*
	(0.03)	(0.03)	(0.01)	(0.01)
R^2	0.70	0.67	0.30	0.31
Observations	29,480	29,480	29,480	29,480
Dependent variable mean	0.46	0.46	0.04	0.04
municipality fixed effects	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

B Robustness Checks

B.1 Alternate DV Codings

The following shows the robustness of results to a variety of alternate constructions of the dependent variable. Overall, they provide evidence that findings are not an artifact of how the panel data were constructed.

B.1.1 Dropping Uncorroborated Groups

One concern about using a *narcoblog* is that the information is lower quality and unverified, which may lead to inflating the number of criminal groups present in a given municipality. To partially account for this, I drop the small number of groups that could not be corroborated using mainstream (e.g., non-blog) press sources.

Table B8: Kingpin Removals, Fuel Theft, and Criminal Groups, Corroborated

	(1)	(2)
Kingpin Removal	0.23***	
	(0.03)	
Gas Pipeline x Price		0.11***
		(0.03)
PAN party mayor	-0.01	-0.02
	(0.03)	(0.03)
Marijuana Hectares	-0.15***	-0.16***
	(0.03)	(0.03)
Poppy Hectares	0.01	0.02
	(0.03)	(0.03)
R^2	0.57	0.57
Observations	29,480	29,480
Dependent variable mean	0.24	0.24
municipality fixed effects	✓	✓
year fixed effects	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

B.1.2 Dropping Minor Groups

In this section I show robustness to dropping the least established groups in the dataset, where the risk of reporting bias will be highest. I proxy this dropping any groups that appeared fewer than 10 times in *Borderland Beat*.

B.1.3 Dropping Umbrella Groups

Eight groups in my dataset are umbrella groups, representing a formalized alliance, typically to fight against a common enemy. For example, the United Cartels, a coalition of groups like the Viagras and the Cartel de Tepalcatepec, fights the CJNG in Michoacán. Since individual group affiliations are often not mentioned, I treat umbrellas as a single cell. While imprecise, the following tables show that results are robust to dropping these umbrella groups entirely.

Table B9: Kingpin Removals, Fuel Theft, and Criminal Groups, Dropping Smallest Groups

	(1)	(2)
Kingpin Removal	0.22***	
	(0.03)	
Gas Pipeline x Price		0.10***
		(0.03)
PAN party mayor	-0.02	-0.03
	(0.02)	(0.02)
Marijuana Hectares	-0.14***	-0.14***
	(0.03)	(0.03)
Poppy Hectares	0.008	0.01
	(0.03)	(0.03)
R^2	0.56	0.56
Observations	29,480	29,480
Dependent variable mean	0.22	0.22
municipality fixed effects	✓	✓
year fixed effects	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

Table B10: Kingpin Removals, Fuel Theft, and Criminal Groups, Dropping Umbrella Groups

	(1)	(2)
Kingpin Removal	0.24***	
	(0.03)	
Gas Pipeline x Price		0.11***
		(0.03)
PAN party mayor	-0.02	-0.03
	(0.03)	(0.03)
Marijuana Hectares	-0.14***	-0.15***
	(0.03)	(0.03)
Poppy Hectares	0.01	0.01
	(0.03)	(0.03)
R^2	0.57	0.57
Observations	29,480	29,480
Dependent variable mean	0.23	0.23
municipality fixed effects	✓	✓
year fixed effects	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

B.1.4 Testing for Group Presence

While this paper deals with the rising number of groups operating in municipalities, we may also be interested in whether any criminal organization operates in a given territory. This is particularly helpful if the concern is that rising levels of violence may lead to greater reporting on inter-cartel fighting. While difficult to fully account for this, the bias should be particularly problematic when trying to identify the *number* of groups in an area, compared to simply whether any criminal group operated. I show results hold using as a dependent variable an indicator for whether at least one organization of different types could be tied to a municipality.

Table B11: Kingpin Removals and Criminal Group Presence (Binary)

	Major (1)	Minor (2)	Emergence (3)	Expansion (4)
Kingpin Removal	0.46***	0.14***	0.05***	0.05***
	(0.01)	(0.01)	(0.007)	(0.008)
PAN party mayor	-0.005	-0.008	-0.01*	-0.001
	(0.008)	(0.007)	(0.005)	(0.006)
Marijuana Hectares	-0.004	-0.02***	0.009*	-0.02***
	(0.005)	(0.005)	(0.004)	(0.006)
Poppy Hectares	0.01*	0.005	-0.01*	0.005
	(0.006)	(0.005)	(0.005)	(0.006)
R^2	0.63	0.51	0.29	0.30
Observations	29,480	29,480	27,024	27,024
Dependent variable mean	0.15	0.10	0.04	0.06
municipality fixed effects	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

B.1.5 Without Backfilling

In case the decision to backfill the data between group appearances in the same municipality impacts results, here I show findings using only years that a group was known to operate in a particular municipality.

Table B12: Gas Pipelines and Criminal Group Presence (Binary)

	Major (1)	Minor (2)	Emergence (3)	Expansion (4)
Gas Pipeline x Price	0.03**	0.03***	0.009	0.01*
	(0.01)	(0.009)	(0.006)	(0.006)
PAN party mayor	-0.02*	-0.01+	-0.01*	-0.003
	(0.009)	(0.007)	(0.005)	(0.006)
Marijuana Hectares	-0.01*	-0.02***	0.008+	-0.02***
	(0.006)	(0.005)	(0.004)	(0.006)
Poppy Hectares	0.02*	0.007	-0.01*	0.006
	(0.007)	(0.005)	(0.005)	(0.006)
R^2	0.54	0.50	0.28	0.30
Observations	29,480	29,480	27,024	27,024
Dependent variable mean	0.15	0.10	0.04	0.06
municipality fixed effects	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

Table B13: Kingpin Removals, Fuel Theft, and Criminal Groups, Without Backfilling

	Major		Minor	
	(1)	(2)	(3)	(4)
Kingpin Removal	0.64***		0.20***	
	(0.02)		(0.03)	
Gas Pipeline x Price		0.04*		0.10***
		(0.01)		(0.03)
PAN party mayor	-0.010	-0.03*	-0.02	-0.02
	(0.01)	(0.01)	(0.02)	(0.03)
Marijuana Hectares	-0.03**	-0.04***	-0.12***	-0.13***
	(0.01)	(0.01)	(0.03)	(0.03)
Poppy Hectares	0.03*	0.04**	-0.01	-0.01
	(0.01)	(0.01)	(0.03)	(0.03)
R^2	0.61	0.56	0.52	0.51
Observations	29,480	29,480	29,480	29,480
Dependent variable mean	0.22	0.22	0.22	0.22
municipality fixed effects	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

B.2 Alternate Kingpin Treatments

In the main text, I treat a municipality as affected by a kingpin removal if it experienced a leadership capture or arrest within the past three years. In this section, I show that results hold using an alternate specification, with any time after a kingpin treatment considered “treated". I additionally show results with a more restrictive coding of what group presence means – that a targeted group was present in the year of the kingpin removal (rather than in year t or $t-1$).

Table B14: Kingpin Removals and Criminal Groups (Always ‘On’)

	Major (1)	Minor (2)	Emergence (3)	Expansion (4)
Kingpin Removal (On)	0.82***	0.30***	0.12***	0.10***
	(0.03)	(0.04)	(0.01)	(0.02)
PAN party mayor	-0.03+	-0.02	-0.01+	-0.004
	(0.01)	(0.03)	(0.008)	(0.01)
Marijuana Hectares	-0.03**	-0.15***	0.001	-0.04**
	(0.01)	(0.03)	(0.009)	(0.01)
Poppy Hectares	0.03*	0.01	-0.02	0.0002
	(0.01)	(0.03)	(0.01)	(0.02)
R^2	0.68	0.57	0.31	0.28
Observations	29,480	29,480	27,024	27,024
Dependent variable mean	0.25	0.24	0.06	0.09
municipality fixed effects	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

Table B15: Kingpin Removals and Criminal Groups, Affected=Present Year Of

	Major (1)	Minor (2)	Emergence (3)	Expansion (4)
Kingpin Removal (presence=t)	0.78***	0.23***	0.08***	0.04*
	(0.02)	(0.03)	(0.01)	(0.02)
PAN party mayor	-0.02	-0.02	-0.01+	-0.004
	(0.01)	(0.03)	(0.008)	(0.01)
Marijuana Hectares	-0.03**	-0.15***	0.0006	-0.04**
	(0.01)	(0.03)	(0.009)	(0.01)
Poppy Hectares	0.04**	0.01	-0.02	0.002
	(0.01)	(0.03)	(0.01)	(0.02)
R^2	0.70	0.57	0.31	0.28
Observations	29,480	29,480	27,024	27,024
Dependent variable mean	0.25	0.24	0.06	0.09
municipality fixed effects	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

B.3 Alternate Fuel Theft Treatments

This section presents several alternative measures of the profit opportunities "treatment." Results are robust to using a more flexible measure of profit opportunities, log distance to a pipeline, which better accounts for municipalities that are near (but do not intersect with) pipelines. I additionally show results using a pre/post indicator for the 2017 deregulation, which acted as a quick shock to gas prices. This accounts for a limitation with my data: because it only runs from 2009 to 2020, we do not observe criminal groups before subsidies were removed. I additionally show that results are robust to interacting gas prices with a binary indicator for the presence of a pipeline, to ensure that results are not a function of municipality size. Finally I show that results are robust to using all pipelines constructed in Mexico, rather than only those built before the militarization of the conflict.

Table B16: Gas Pipeline Presence and Criminal Groups

	Major (1)	Minor (2)	Emergence (3)	Expansion (4)
Pipeline Presence x Price	0.24***	0.48***	0.04	0.21***
	(0.06)	(0.12)	(0.04)	(0.05)
PAN party mayor	-0.04*	-0.02	-0.02*	-0.006
	(0.02)	(0.03)	(0.008)	(0.01)
Marijuana Hectares	-0.04***	-0.16***	-0.001	-0.04**
	(0.01)	(0.03)	(0.009)	(0.01)
Poppy Hectares	0.04**	0.02	-0.02	0.003
	(0.01)	(0.03)	(0.01)	(0.02)
R^2	0.63	0.57	0.30	0.28
Observations	29,480	29,480	27,024	27,024
Dependent variable mean	0.25	0.24	0.06	0.09
municipality fixed effects	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

Table B17: Gas Pipeline x Post-2017 and Criminal Groups

	Major (1)	Minor (2)	Emergence (3)	Expansion (4)
Gas Pipeline x Post-2017	0.03***	0.04**	0.0006	0.02**
	(0.008)	(0.01)	(0.004)	(0.006)
PAN party mayor	-0.04*	-0.02	-0.02*	-0.005
	(0.02)	(0.03)	(0.008)	(0.01)
Marijuana Hectares	-0.04***	-0.16***	-0.001	-0.04**
	(0.01)	(0.03)	(0.009)	(0.01)
Poppy Hectares	0.04**	0.01	-0.02	0.002
	(0.01)	(0.03)	(0.01)	(0.02)
R^2	0.63	0.57	0.30	0.28
Observations	29,480	29,480	27,024	27,024
Dependent variable mean	0.25	0.24	0.06	0.09
municipality fixed effects	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

Table B18: Distance to Pipeline and Criminal Groups

	Major (1)	Minor (2)	Emergence (3)	Expansion (4)
Distance (log) x Price	-0.04**	-0.09**	-0.02*	-0.06***
	(0.01)	(0.03)	(0.009)	(0.01)
PAN party mayor	-0.04*	-0.02	-0.02*	-0.006
	(0.02)	(0.03)	(0.008)	(0.01)
Marijuana Hectares	-0.04***	-0.16***	-0.002	-0.04**
	(0.01)	(0.03)	(0.009)	(0.01)
Poppy Hectares	0.05**	0.02	-0.02	0.004
	(0.01)	(0.03)	(0.01)	(0.02)
R^2	0.63	0.57	0.30	0.28
Observations	29,480	29,480	27,024	27,024
Dependent variable mean	0.25	0.24	0.06	0.09
municipality fixed effects	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

Table B19: Gas Pipelines (2020) and Criminal Groups

	Major (1)	Minor (2)	Emergence (3)	Expansion (4)
Gas Pipeline (2020) x Price	0.05**	0.09**	0.008	0.05***
	(0.02)	(0.03)	(0.009)	(0.01)
PAN party mayor	-0.04*	-0.02	-0.02*	-0.006
	(0.02)	(0.03)	(0.008)	(0.01)
Marijuana Hectares	-0.04***	-0.16***	-0.001	-0.04**
	(0.01)	(0.03)	(0.009)	(0.01)
Poppy Hectares	0.04**	0.02	-0.02	0.003
	(0.01)	(0.03)	(0.01)	(0.02)
R^2	0.63	0.57	0.30	0.28
Observations	29,480	29,480	27,024	27,024
Dependent variable mean	0.25	0.24	0.06	0.09
municipality fixed effects	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓

$***p < 0.001, **p < 0.01, *p < 0.05, +p < .01$. Robust SEs clustered by municipality. Controls for mayoral party, poppy eradication, and marijuana eradication, plus state-year linear time trends.

B.4 Heterogenous Treatment Effects

Recent research has demonstrated bias in the results of two-way fixed effects designs with heterogenous treatment effects. To account for this, I show the results of the De Chaisemartin and d'Haultfoeuille (2020) estimator. I additionally show the results using the Callaway and Sant'Anna (2021) estimator. The latter requires that units cannot fall out of treatment, so results use the secondary specification of the independent variable: a kingpin capture affecting a given municipality means all subsequent years are considered treated. As in the main text, there is some evidence of pre-trends, which may follow from the fact that weaker groups are more likely to experience kingpin removals. Using De Chaisemartin and d'Haultfoeuille (2020) I include controls for poppy and marijuana eradication and mayoral party; I do not include state linear time trends due to modeling limitations. With Callaway and Sant'Anna (2021) I do not include controls due to non-convergence.

B.4.1 Chaisemartin and D'Haultfoeuille

Figure B2: Chaisemartin and D'Haultfoeuille, Major Cartels and Minor Groups

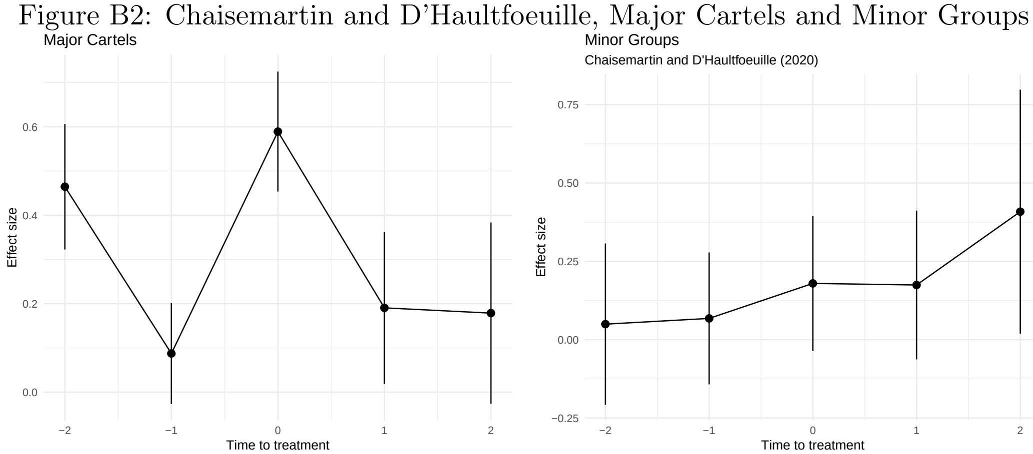
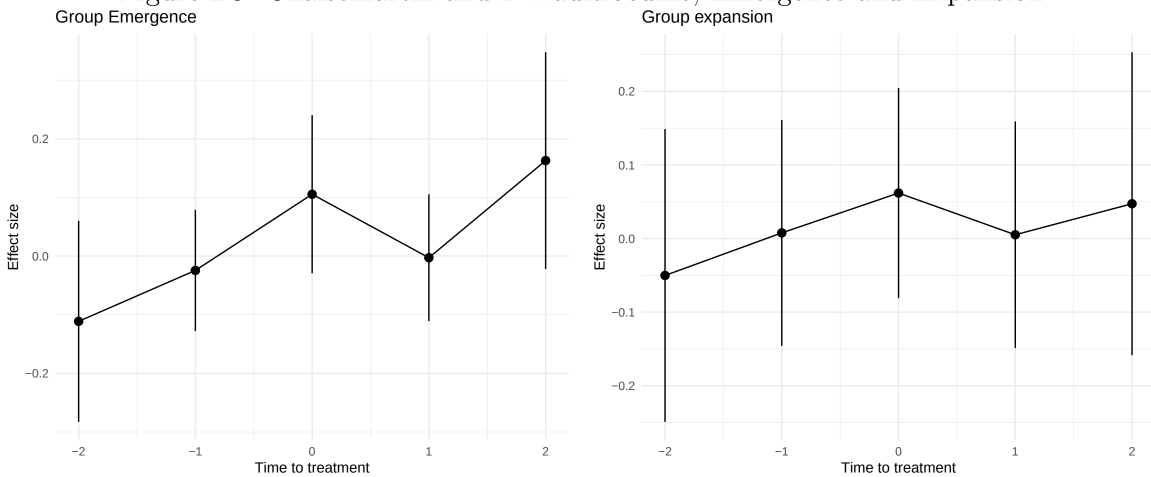


Figure B3: Chaisemartin and D'Haultfoeuille, Emergence and Expansion



B.4.2 Callaway and Sant'Anna

Figure B4: Effects

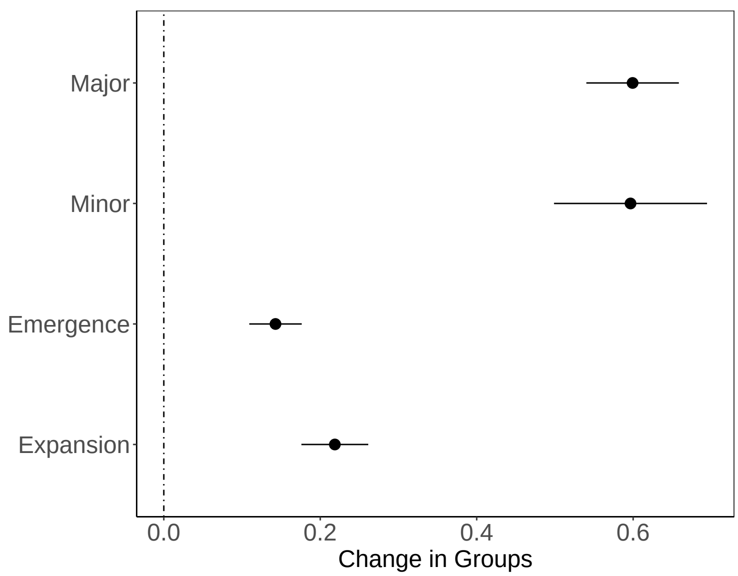


Figure B5: Major Groups

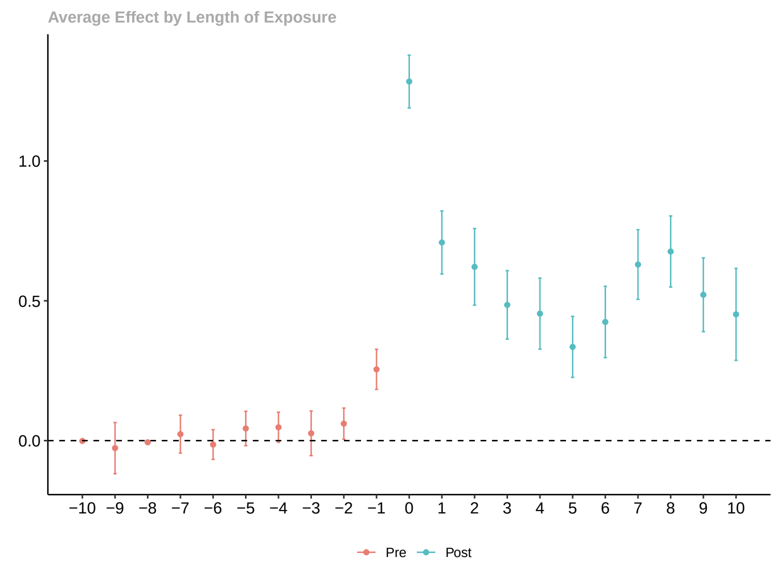


Figure B6: Minor Groups

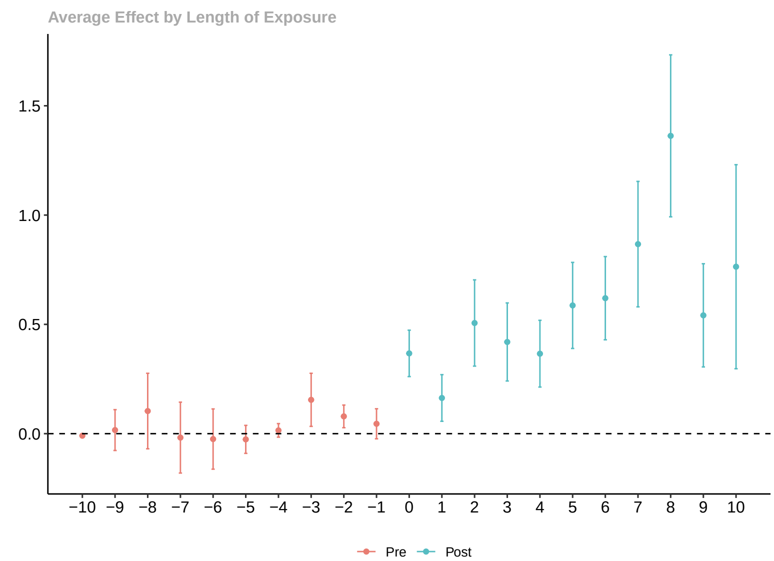


Figure B7: Group Emergence

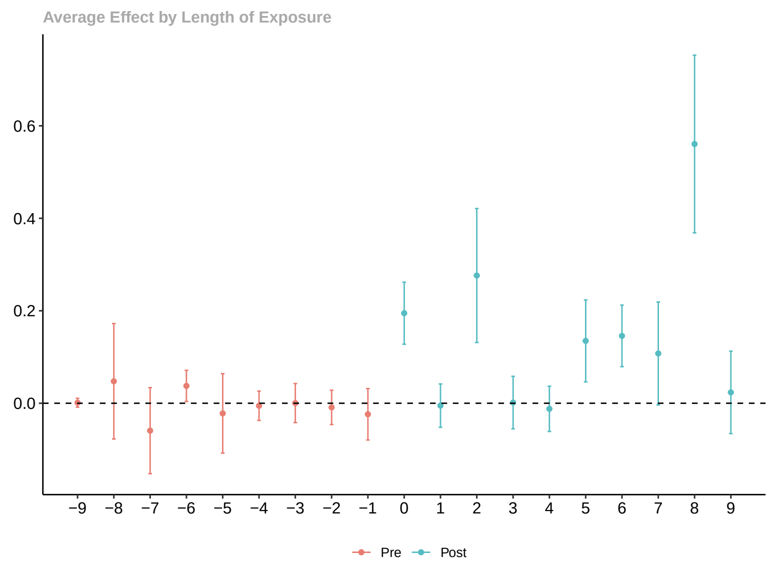
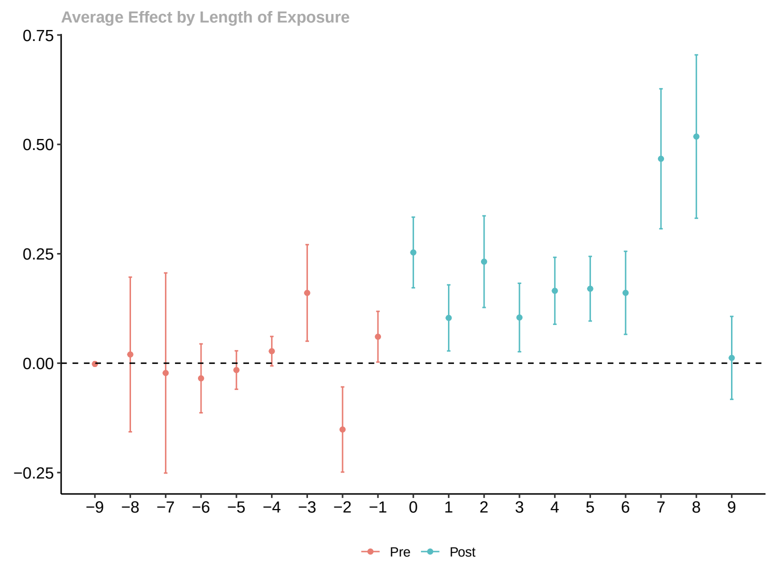


Figure B8: Group Expansion



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