Competition and Self-Regulation in Illegal Sectors[‡]

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Abstract

This paper examines how market concentration influences violence in illegal sectors. Leveraging unique intelligence data from Naples' retail drug market, we show that larger gangs are less violent. We then develop a quantitative model of an oligopolistic market in which gangs strategically decide whether to engage in conflict, balancing expected additional profits from gaining market share against the costs of increased violence and police presence. We estimate the model using original data on drug seizures, inter-gang conflict, and police presence. We find that larger gangs self-regulate to avoid a strong police reaction, suggesting unintended consequences for policies aimed at fragmenting criminal organizations. Simulations reveal a non-linear relationship between market concentration and violence.

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1 Introduction

Illegal markets operate on a massive scale and impose substantial costs on society.[1] From illicit substances to human trafficking, these activities not only impose large enforcement costs, but also have direct negative effects on different sectors of the economy (e.g. Pinotti, 2015; Monteiro & Rocha, 2017; Alesina et al., 2019; Melnikov et al., 2020). To disrupt these markets, traditional enforcement strategies have typically relied on crackdowns and extensive arrests. These interventions operate under the assumption that fragmenting criminal organizations weakens them and mitigates their negative impact on society. However, these interventions often backfired, generating dramatic increases in violence (e.g. Chicago 1990s Fox et al., 2015; Mexico 2006 Dell, 2015). The problem is that when designing these interventions, policymakers ignore the *firm* nature of these organizations and the relationship between competition and violence.

This paper studies how market concentration influences violence in illegal sectors (a classic question in the field, since Buchanan, 1973). This relationship depends on two key factors: how violence changes with the number of gangs and with gang size. When deciding whether to engage in violence, gangs face a trade-off. On one hand, they may win the conflict, force rival gangs to leave the area, and increase their market share. On the other hand, they generate violence in the area, discouraging consumers and attracting police attention. The relationship between market concentration and violence depends on how the two factors affect these dynamics.

To study this trade-off, we leverage new data on the retail drug market in Naples. The horizontal structure with multiple independent gangs makes this an ideal setting. We proceed in three steps. First, we focus on the relationship between gang size and violence. Exploiting variation in average gang size across areas, combined with an event-study and an IV, we show that larger gangs are less violent. Second, we develop an equilibrium model of gang competition that incorporates three key elements: a nested logit demand structure, a fighting game with uncertainty (building on Donohue & Levitt, 1998), and endogenous demand and police responses to violence. The unique combination of administrative data on drug seizures and police arrests with intelligence

[1] Criminal groups generated an estimated $3.6-$4.8 trillion in revenues during 2015/2016, approximately 7% of global GDP. Illegal drug trafficking alone accounts for more than $500 billion in annual revenues, a figure larger than the global smartphone industry's total revenue. Source for total revenues: estimate by Global Initiative against Transnational Organized Crime (Global Initiative). Source for estimate drug trafficking revenues: Kar and Spanjers (2017). The global revenue in the "Smartphones" segment of the consumer electronics market was $450 billion in 2019. Source: Statista. Drug trafficking linked to approximately half of all homicides in the European Union, imposing substantial societal costs. Source: Eurojust on europol data. EU cost of responding to illegal drugs was approximate 34 billion euros in 2013 (EMCDDA, 2013), with the direct cost of their homicides alone estimated to be between 500 million euros and 5 billions, depending on the statistical value of life (authors calculations on data from EU - Policy deparment, 2013 on gang related homicides in EU

data on gang presence and inter-gang fights allows us to estimate the model and measure the different incentives underlying the trade-off. Third, we use the estimated model to explore the relationship between market concentration and violence by counterfactually changing the market's structure and evaluating policies aimed at fragmenting criminal groups.

We draw on an original dataset on the retail drug market in Naples province from 2015 to 2022, constructed by combining intelligence, administrative, and survey data from multiple sources. The primary data source is a set of matrices showing gangs presence in this market across areas and years. This is enriched with a comprehensive list of fights between gangs from investigations, including information about the involved parties, year, contested area, and the winner. To measure violence and police activity, we use intelligence data on homicides, attempted homicides, and arrests for different crimes. To study fighting incentives in the retail drug market, we use confidential administrative data on drug seizures from the antidrug authority, containing geolocalized information on approximately 14,000 seizures during the sample period, along with a random sample of chemical analyses of the seized drugs to measure their quality. The dataset is completed with intelligence data on average retail and wholesale prices, together with survey data on consumer and area characteristics. Thorough the paper, we measure the dimension of a gang with the number of areas in which it is active (gang *scale*), and define a gang to be large if its scale is higher than 3–the 90th percentile.[2]

The data reveals that areas with smaller gangs experience significantly higher levels of violence. In areas populated exclusively by small gangs, the probability of gang homicides reaches approximately 25%, while areas with large gangs see this probability drop to around 10%. This pattern holds consistently across various violence measures, including general homicides and gang fights. Importantly, these results remain quantitatively similar when controlling for the number of active gangs and area and year fixed effects, suggesting that our findings cannot be explained by fixed characteristics of locations or time periods. After controlling for fixed effects, one-unit increase in average gang scale is associated with approximately 6-10% reduction in homicide probability and a 36% decrease in the likelihood of inter-gang fights.

We then investigate how variation in average gang size, due to the entry of new gangs, creates marginal changes in violence using an event-study design. The entry of a new gang in the area is associated with an approximately 16% increase in the probability of gang homicide during the first period, compared to the pre-entry period, and a 75% increase in the second period. This

[2]We use the terms scale, size, dimension independently in this paper. We are aware that when we talk about "size" of firms, we usually refer to the number of employees, revenues, or other type of measures. However, the number of areas is the only measure of size we can directly observe from the data. Moreover, this measure is often correlated to more common ones of firm size which, unfortunately, are unobserved.

average effect masks substantial heterogeneity based on gang size. The increase in violence is more pronounced when a small gang enters the area (53% and 108%). Conversely, the entry of a large gang is associated with a decrease in the probability of gang homicide of approximately -8% and -13% in the first and second period respectively. As before, this evidence is robust to different measures of violence (e.g. probability of homicide, number of homicides, and probability of fights) and the inclusion of area and year fixed effects. To address the endogeneity of the entry choice, we use a shift-share instrument to predict a set of "exogenous" entries. Our instrument exploits the opportunity created when gangs exit an area for reasons unrelated to fighting (such as enforcement activity), combined with the proximity of potential entrant gangs to that area in the previous period. Using these predicted entries, rather than actual entries, in event-study analyses confirms the previous results: the entry of small gangs increases the probability of gang homicides, while the entry of large gangs decreases it. We therefore conclude that larger gangs are less violent.

To understand the mechanism behind this result, we explore fighting incentives in the retail drug market. We identify three key facts characterizing this market. First, consumers dislike violence. Second, larger gangs have a higher probability of winning conflicts. Third, fights involving larger gangs generate more pronounced violence, and therefore attract more police attention. These empirical facts suggest three potential mechanisms: (i) a *deterrence* mechanism, whereby smaller gangs, acknowledging their diminished probability of prevailing in conflicts against larger counterparts, strategically avoid confrontation; a (ii) *demand* mechanism, where because of the higher amount of violence generate by fights involving larger gangs, these have an stronger negative impact on demand, reducing fighting incentives; and a (iii) *self-regulation* mechanism, whereby larger gangs, internalizing the stronger response of the regulator, the police, strategically self-regulate to minimize this negative externality.

To quantify the fighting tradeoffs, we develop a new model of the retail drug market with violent competition. Formally, we combine a nested logit demand structure (similar to Goldberg, 1995; Goldberg & Verboven, 2001) with a fighting game, building on Donohue & Levitt, 1998. Geographically dispersed consumers choose where to look for drugs based on transportation costs, fights, and unobserved preferences. In line with the demand mechanism, we allow fights involving small and large gangs to have an heterogenous impact on demand. Gangs differ in their initial scale (determined outside the model) and solve a static two-stage game. In the second stage, given the market structure, demand, and distribution of police attention, gangs realize profits. In the first stage, they shape the market structure by deciding whether to fight against other gangs in a sequential game (similar to an entry deterrence game, as in Salop, 1979). When fighting, gangs

lower demand and increase police attention, but if they win, they force their competitor out of the area. Fights are a negative externality, impacting demand for all the gangs present in the area.

Nature randomly gives one gang in each potential pair the opportunity to fight first. This gang chooses whether to fight, and then the other decides whether to respond or leave. Fights emerge as an equilibrium when both gangs can credibly commit to fight and fighting is more profitable than simply exiting the market. This simple two-gang, one-area game has multiple equilibria, but unique equilibrium in the fighting outcome (similar to Reiss & Bresnahan, 1990; Berry, 1992 on the number of entrants in an entry game). However, the overall model (as a set of connected fighting games) has multiple equilibria. The fighting outcome probabilities are determined by a step fighting mechanism with an observable component–the fighting ability–and an unobservable component, which introduces randomness in fight outcomes. In line with the previously presented facts, we allow gangs of different sizes to have heterogeneous fighting abilities, which influence their probability of winning fights. In this simple model, police is, essentially, a function. Hence, the regulator's reaction is predictable. In particular, there is a fixed amount of attention in each area, and police react to fights heterogeneously based on the scale of the gangs involved, consistent with the presented evidence. Police presence is a fixed cost in the gangs' profit. Therefore, when deciding whether to fight, gangs trade off the expected additional profits from gaining larger market share against costs stemming from lower demand and higher police presence.

We use new confidential intelligence and administrative data on the retail drug market to estimate the model in four steps. First, we estimate demand parameters by exploiting variation in seized drug quantities across areas, estimating the across-nests log-linear demand function. The main parameter in this second step is the heterogeneous consumer dis-utility from fights, which will then determine the demand cost of fights involving only small gangs and fights involving also large ones. Here we face a selection problem: changes in drug seized at the fight outbreak is the composition of two effects (i) the direct effect of the fight on the quantity sold, and (ii) the change in selection/seizures due to the fight. To solve this endogeneity concern, we use a control function method. Estimation follows a two step approach. First, we estimate the selection equation exploiting the correlation between the number of seizures and an IV: the number of arrests by local police.[3] Second, we estimate the log-linear demand *controlling* for selection. In the second step, we estimate fighting parameters via simulated method of moments, using data

[3]This is a proxy of the attention of the local police, which is relevant for drug seizures, but unlikely to have any impact on the dynamics of the drug market. Indeed, as detailed in section 2, this enforcement agency focuses on local law enforcement, traffic control, and urban regulations enforcement. Therefore, it is very unlikely to investigate drug-related crimes.

on fighting outcome probabilities. In the third step, we estimate police reaction with changes in the number of arrests following fight outbreaks in a simple difference-in-difference. To conclude, we estimate the remaining parameters with MLE.

For the elasticity of demand to fights, our estimates confirm the negative and heterogeneous impact of fights. Specifically, a fight involving only small gangs decreases quantity by approximately 10%, while a fight involving at least one large gang by approximately 32%–equivalent to a 40% increase in price. The 8.4% higher probability of winning fights is matched with an higher fighting ability for larger gangs. In line with most fights ending in draws (71%), we estimate a large step of the fighting process and standard deviation of the fighting shock, determining an high unpredictability of the fighting process. In line with fights involving larger gangs generating more violence, we find that police attention increases by 15% when the fight involves only small gangs, and by 437% if at least one large gang was involved. Finally, we estimate a large police cost, with a decrease in approximately 20% of average profits associated with a 1% increase in police attention.

The model, while simple, has a good fit with the observed data. We find a robust positive correlation between observed drug quantity share seized and predicted quantities, even when controlling for drug, year, and city fixed effects. As for fights, we find a positive correlation between realized fighting probabilities and predicted ones. In line with the model predictions, we find an higher probability of fights occurring when expected profits from fighting, relative to the outside option – peace or exit – are higher. Importantly, both observed and predicted data show consistent patterns: more valuable areas have more fights, as areas with more gangs, and areas with larger and more diverse gangs show lower fighting probabilities. This suggests the model captures key determinants of fighting decisions.

We use the model to test competing explanation for the observed lower fighting propensity of large gangs and determine the relationship between market concentration and violence. In the data, large gangs show a 59% lower fighting propensity. The model predicts a similar difference (57%), which is expected given the MLE estimation on fighting probabilities. To test the mechanisms, we run counterfactual simulations. First, we test the deterrence mechanism by equalizing fighting abilities, but this has little effect on fighting propensities. This suggests deterrence is not the driving mechanism, which is logical given the low fighting premium (+8%) and high draw probability (71%). When we equalize the elasticity of demand to fights, this difference decreases slightly, suggesting that demand reaction may play a limited role in explaining the different fighting propensity. However, when we set police reaction to be the same for both types of fights, the pattern reverses completely, with large gangs becoming 1% more likely to fight than small gangs.

This evidence supports the self-regulation mechanism: negative behaviors by larger gangs generate a stronger reaction from the regulator–in this case, the police. Gangs internalize this reaction and choose to fight less.

To conclude, we study the relationship between market concentration and violence. Specifically, we randomly merge gangs to increase market concentration from an atomistic market to a monopoly. Our simulations reveal a non-linear relationship between market concentration and violence. The atomistic market is moderately violent, with a relatively high probability of fights occurring. As market concentration begins to increase and some large gangs appear, the probability of fights increases even further. Introducing very few large players into a continuum of very small gangs disrupts the equilibrium, both by substantially decreasing the unpredictability of fights and by creating gangs sufficiently large to cover the fixed costs of fighting. This pattern continues until we reach a first tipping point. Beyond this point, the further we increase market concentration, the lower the predicted probability of fights becomes. Here, the additional increase in the predictability of fights is not sufficient to counter the combined effects of fewer gangs in the market and the increasing costs of fighting. At the other extreme of the market concentration distribution, this relationship reverses again, due to expected benefits from fighting increasing non-linearly. At complete monopoly, violence naturally disappears as there are no competitors.

This non-linear relationship reveals why traditional gang enforcement strategies often produce counterproductive results and highlights the need for context-specific policy approaches. While targeting slightly larger gangs in highly fragmented markets may effectively reduce violence by restoring atomistic competition, the same strategy in oligopolistic markets can backfire by fragmenting large organizations into smaller, more violent groups that move markets from peaceful concentrated states toward highly violent equilibria. This explains why many aggressive enforcement campaigns have increased rather than decreased violence, as in numerous real-world examples (e.g. Chicago 1990s Fox et al., 2015 and Mexico 2006 Dell, 2015). The fundamental insight is that identical enforcement actions can produce opposite violence outcomes depending on the initial market structure, making tailored, context-aware strategies essential for successful crime reduction without the violence cost.

This paper is mainly related to the literature on the "organization" of crime, studying internal organization of criminal groups (e.g. Polo, 1995; Levitt & Venkatesh, 2000; Mastrobuoni & Patacchini, 2012; Campaniello et al., 2016), expansion in legal markets (e.g. Gambetta & Reuter, 2017; Le Moglie & Sorrenti, 2020; Mirenda et al., 2022), and determinants of market structure in illegal sectors (e.g. transaction costs in Cook et al., 2007, absence of regulatory institu-

tions in Schelling, 1967; Donohue & Levitt, 1998, and moral hazard in Galenianos et al., 2012; Galenianos & Gavazza, 2017). More closely related to the relationship between competition and violence, Levitt & Venkatesh, 2000 suggests that fights may be very costly for gangs. Similar conclusions are drawn by Brown et al., 2024 in the extortion market in El Salvador, where they document an increase in extortion rate at the aftermath of a pact between gangs which reduced competition and violence. Blattman et al., 2024 points towards the same direction, showing that gangs in Colombia have incentives to reduce external violence to protect drug rents from police activity. This paper builds on these insights on the costs of fights to study the violent competition across gangs. The closest papers in the literature are Dell, 2015 and Bruhn et al., 2021. Dell, 2015 documents an increase in violence following crackdowns that have weakened incumbent gangs in Mexico, while Bruhn et al., 2021 exploits geographic variation in gangs activities in Chicago and shows an increase in violence due to gang competition when a new gang enters a new city block. This paper builds upon these important contributions by examining more in detail gang competition and by providing a structural framework to study the relationship between market concentration and violence.

The paper is structured as follows. Section 2 introduces the setting of the study and the data. In section 3, we present evidence on the relationship between gang scale and violence. Section 4 document key facts about the retail drug market and build the structure of the model. Section 5 describes the estimation procedure, discusses identification of the model parameters, and summarizes the estimation. These are used to construct counterfactual scenarios in Section 6. Section 7 concludes.

2 Setting and Data

2.1 Setting

Organized crime has a long history in the province of Naples, with some evidence of gang behavior going back to the 17th century, and the first written proof of its existence dating back to the 1800s (Barbagallo, 2014; Sales, 2022). The historian Marc Monnier describes these gangs as "a kind of schismatic police" that controlled Naples' prisons, markets, and illegal gambling houses (Monnier, 1862). These organizations experienced a significant evolution in the post-World War II period, transforming from a local phenomenon into an international criminal network involved in cigarette smuggling, drug trafficking, and other illicit activities (Sales, 1994, 2022). These new opportunities, along with business from the post-earthquake reconstruction follow-

ing the 1980 disaster, provided the gangs with immense financial resources. At the same time, they created incentives for heightened competition for dominance among rival groups, leading to the first great gang fight in 1980 (Marrazzo, 2005), which resulted in approximately 1,000 homicides in six years.

From the 1990s to today, organized crime in Naples has maintained its horizontal structure with multiple independent gangs (Brancaccio & Martone, 2019). These clans are usually smaller than other Italian mafia groups and are characterized by lower internal organization and more intense conflicts (Catino, 2014). These characteristics make most of these gangs similar to some in North and South America (Dugato et al., 2020). This criminal ecosystem is structured around two dominant cartels. While these two cartels try to maintain control over distinct macro-areas of metropolitan Naples, they are mainly composed by a complex network of small satellite groups that exercise tight territorial control over specific neighborhoods and districts. Thereofore, this dichotomous structure is marked by constant instability and fluid dynamics. Even within areas of exclusive cartel control, precarious equilibriums persist due to frictions between gangs–both across and within cartels–and the emergence of new criminal groups (for example of these frictions, please refer to reports from DIA, 2015 to DIA, 2022). As a result, this ecosystem is extremely violent, with mafia-related homicides accounting for 60-70% of all intentional homicides in its territories, significantly exceeding the national average of 10-15% (Catino, 2014). The scale of this "system" is massive, with activities in numerous countries (DIA, 2020), and thousands of affiliates divided into more than 100 gangs.

Today, these gangs engage in a wide range of criminal enterprises, with their core activities including drug trafficking, extortion, infiltration of public contracts, arms trafficking, counterfeiting, usury, protection rackets, prostitution, illegal waste disposal, and money laundering (Barbagallo, 2014). Estimated revenues from all these activities amount to approximately 9 billion euros annually (Transcrime, 2013). Despite this wide diversification, drug trafficking remains their main area of activity, accounting for more than 50% of estimated revenues (Eurispes, 2005). This is consistent with other criminal groups worldwide, as the drug business is often recognized as the most lucrative market for criminal organizations (Reuter, 2014).

Neapolitan gangs involved in the drug market tend to control the retail market by enlisting low-level criminal labor. Direct management of drug dealers creates an efficient distribution system and generally adheres to precise territorial boundaries with other gangs (Becucci, 2004). The exact production and distribution process of drugs varies dramatically among different gangs. However, it develops around some common grounds. International brokers, allied with the previously mentioned cartels, or operating independently, usually import raw drugs from other con-

tinents (mostly from Africa and South America - DCSA, 2024). When the broker arrives with the delivery, each gang takes its share, then cuts, packages, and prepares the drug for the retail market (Gribaudi et al., 2009). Local drug dealers then sell the drugs on the street, or, more recently, online. The prevailing method for retail drug sales consists of *piazze di spaccio* (literally, drug dealing squares), which are well defined and organized areas dedicated to the sales of illegal drugs, and their control has often fueled fights between gangs, resulting in numerous casualties (Catino, 2019). The management of dealers is very heterogeneous: the majority receive a fixed salary, some receive daily payment based on sales, while others operate as independent entrepreneurs. As well as paying salaries, a gang's common fund is often used to pay for assistance and legal advice, the "tools of the trade" (weapons, cars, phones, etc.), and health and housing emergencies that members may face (Catino, 2019).

As an example of how well organized retail drug distribution is, here we cite one of these dealers (Ferrillo, M., *Spacciatore o spacciato?* Torino: Gruppo Abele (unpublished 2000, p. 39), from Becucci, 2004):

[...] street dealers are called to meet in a large apartment where drugs are distributed along with instructions. Everybody is assigned a precise spot to stand and somebody warns the dealer right away in case of danger when the police are on the way.

As a result, we should think about the retail drug market in the province of Naples as *competitive*, extremely *well-organized*, and *territorial*.

2.2 Italian enforcement system

Before turning to the actual data, it is worth discussing in few words the organization of the Italian law enforcement system. This system operates through four main police forces, each with distinct responsibilities and jurisdictions. The *Polizia di Stato* (State Police), under the Ministry of Interior, primarily handles urban policing, immigration, highway patrol, and railway security, operating mainly in cities and organized in provincial departments. Therefore, the whole Naples province will have only one State Police division. The *Arma dei Carabinieri*, a military force with police duties under both the Ministry of Defense and Interior, serves as a national gendarmerie force, particularly active in rural areas and small towns. The *Guardia di Finanza*, under the Ministry of Economy and Finance, specializes in financial crime, tax evasion, smuggling, and international drug trafficking. Finally, the *Polizia Locale* (Municipal Police), managed by individual municipalities, focuses on local law enforcement, traffic control, and urban regulations enforcement within specific city boundaries. These forces collaborate through multiple inter-agency

organizations. For example, the Direzione Investigativa Antimafia (DIA), coordinates anti-mafia operations across all police forces, while the Direzione Centrale per i Servizi Antidroga (DCSA) specializes in coordinating drug-related investigations and operations among the various police forces, facilitating information sharing and joint operations against drug trafficking. We use data coming from all these agencies, often together, sometimes separately.

2.3 Data

To study the relationship betwen market structure and violence in the retail drug market, this paper builds a comprehensive dataset on this illegal sector by combining intelligence, administrative, and survey data from different sources.

An important consideration is the data's geographical granularity. All administrative data, by their nature, are at the city-year level. For example, we observe the number of arrests for each city in the province annually, resulting in a single value for the entire city of Naples–a limitation inherent to the data. In contrast, intelligence data are collected at a finer level: city-year for locations outside Naples, and district-year within Naples city itself, which comprises 30 districts. This granularity allows deeper geographical analysis, enabling us to observe metrics like homicides or gang presence for each district in Naples city annually. Notably, most choice variables in the model come from administrative data, while state variables (primarily the matrix of gang presence) derive from intelligence sources. Consequently, we estimate the model at the city-year level and simulate it at the city-year level for Naples province and the district-year level for Naples city.

That being said, our sample is composed by all the cities in the province of Naples (and district within Naples city when available) for the period between 2015 and 2022 included.

Gangs presence The key data for studying the retail drug market is a set of matrices showing gang activity in this market across areas and years. We construct these matrices from intelligence data in two steps. First, using DIA reports (e.g. DIA, 2020), we constructed an initial 0-1 matrix indicating whether a certain gang was mentioned in the report, in a given area, in the semester under study. This reporting could appear in a map (e.g., Figure A1), or in the text (e.g., Figure A2 indicates a gang's entry into a new district). Here it is important to mention our definition of a gang, which we maintain consistently throughout data construction and empirical analysis. Defining gang boundaries is inevitably challenging, perhaps more so than for firms. We define a gang as a group of individuals active in illegal sectors (such as illegal drug trafficking) under a single name, which is clearly *not* a subgroup of another gang. This definition parallels Holmstrom

and Tirole (1989) definition of the firm. While we acknowledge this approach's limitations, the absence of a comprehensive and well-defined gang list, this was, to our knowledge, the only feasible approach. The matrix constructed this way has two main limitations: it is not specific to retail drug market activities, and it records mentions in reports rather than actual presence. Therefore, in the second step, we submitted these matrices to the Neapolitan police to check them. By combining these matrices with their knowledge and intelligence data, they changed them to reflect, as accurately as possible, the retail drug market in each year. This process results in 8 matrices, one per sample year, reflecting different gangs' retail drug market activity across cities–outside Naples city–and districts–within Naples city.

Throughout this paper, we will define a gang as *large* if its scale (i.e., the number of areas in which it is present in the same year) exceeds 3. This classification corresponds to 10% of all gangs in the sample.

Fight matrices The data collection process for the fighting matrices follows the same approach. First, we compiled a list of fights from DIA reports, documenting the involved parties, year, contested area, and the winner. For each conflict, we noted whether the report mentioned a friction–*frizione*–or an actual fight–*guerra*–between the two gangs or groups of gangs. We then submitted these preliminary lists to the Neapolitan police for verification and correction. Using the finalized list, we constructed the fighting matrices (incorporating both frictions and fights).

Drug seizures To measure the retail drug market's size, we use administrative data on drug seizures in Naples province from the Italian antidrug authority (Direzione Centrale Servizi Antidroga). Enforcement agencies must report relevant information to the antidrug authority whenever they seize illegal substances. For all approximately 14,000 seizures during the sample period, we have data on city, date, enforcement authority, seizure type (territorial or maritime; we retain only territorial), type of illegal substance, and quantity seized in kilograms. This paper focuses on three main illegal substances: marijuana, heroin, and cocaine. Thus, we included only seizures of these drugs.[4] Since we are interested in the *amount* of drugs seized, we retain only seizures with non-missing and non-zero quantities (quantities can be zero when the amount seized is negligible in kilograms). We then calculate, for each city, year, and drug type, the total amount of illegal drugs seized, the average quantity seized, and the number of seizures.

[4] Specifically, we included seizures classified as: "cocaine", "crack cocaine", "liquid cocaine" for cocaine; "heroin" for heroin; "hashish", "marijuana", and "cannabis plants" for marijuana.

Other data We complete our set of data with additional sources, such as intelligence data on the chemical analysis of seized drugs, ISTAT data on mortality and population, survey data on drug consumption and prices, survey data on city characteristics (including the activity of municipal police), and data on distances between geographical units. See Appendix D for a detailed description of these data.

Data quality This paper draws mainly on the intersection between two types of data: administrative and intelligence. Under the assumption of completeness and correctness of administrative data, Appendix E assesses the quality of intelligence data by exploring variation in administrative data corresponding to changes in the intelligence data.

3 Descriptive Evidence

This paper studies the relationship between market concentration and violence in illegal sectors. Market concentration can change through two channels: variation in the number of gangs or, holding the number of competitors fixed, variation in gang size. Since the effect of increasing the number of gangs on violence is theoretically straightforward – higher conflict possibilities and greater difficulty sustaining peaceful equilibria, please refer to section E for additional details – here we focus on exploring the relationship between gang size and violence in the data. We then integrate both factors in the structural model presented in Section 4.

In this section, we provide descriptive evidence on the retail drug market in the province of Naples. First, we provide summary statistics regarding the characteristics of the gangs and their presence over time in various areas. Second, we offer evidence on the correlation between violence and the average gang scale. Third, we show how variations in average gang size–due to the entry of new gangs–creates marginal changes in violence in the area.

3.1 Summary statistics and gangs' characteristics

Figure A3 shows the density of our primary measure of gang size: the number of areas in which a gang is present at a given point in time, referred to as the gang *scale*. Approximately 60% of gangs operate within a single area. However, the distribution exhibits a long right tail, indicating the existence of gangs that are active in multiple areas within the same year. Specifically, around 20% of gangs are active in two areas, while the remaining 20% are active in more than two areas.[5]

[5] Importantly, even though the same gang can operate in multiple areas, there appears to be no spatial correlation in their presence. Figure A4 presents the distribution of the Moran's I index calculated for each gang. For gangs

Figures A5 and A6 jointly illustrate the variation that we exploit in this paper. If gangs were to systematically select areas–resulting in the observation of only areas with large gangs or only those with small gangs–or if the distribution of gang scale remained unchanged over time, there would be insufficient variation in gang scale for analysis. However, this is not the case in the province of Naples, making it an optimal setting to explore the relationship between market structure and violence. In Figure A5, we display the cross-sectional variation we exploit in this study. Each point in the scatterplot represents an area, plotted along two dimensions: the number of gangs present in that area and the average gang scale. The color of each dot indicates the maximum scale of the gang in the area. A significant insight from this graph is the absence of systematic sorting. There are areas with a very low number of gangs (or even monopolies) that host gangs of all sizes–some monopolies have small gangs while others have large gangs. There are areas with large gangs that have both many and few gangs, as well as areas that feature numerous small gangs and areas with several large gangs. In other words, there is considerable cross-sectional variation in gang scale and the number of gangs present across different areas. Figure A6 illustrates the variation over time. Specifically, each dot represents an area, positioned along two dimensions: the average gang scale in that area in 2015 and in 2022. The red line represents the 45-degree line; in the absence of temporal variation, we would expect all dots to lie on this line. However, this is not the case. For example, there are areas that had very large gangs in 2015 but no gangs in 2022, and vice versa.

Table 1 presents summary statistics for city-year average values of several characteristics of the market. A few points are worth noting. First, gangs are ubiquitous, with an average presence of 72%. Second, fights between gangs are relatively common, with a 6% average probability. Related to this, the number of homicides is quite high, with gang-related homicides accounting for approximately 50% of the total. Third, the retail drug market reaches massive dimensions, with more than 200 people arrested on average for drug-related crimes, and large quantities of illegal substances seized–up to approximately 4,000 kg of cocaine seized in one year. Fourth, retail prices are substantially above wholesale ones for all drugs in all periods. Fifth, we observe substantial variation in average drug quality–measured as the percentage of pure substance. The actual variation in the specific drugs seized is even larger, as detailed in Appendix E.

Table A1 presents summary statistics on fights between gangs. In our sample, we observe a total of 100 fights, with the contested area identified in 93 cases. In 35 of these fights, a winner exists and is known. Fights typically involve two *groups* of gangs, with an average of 3.25 gangs

present in only one area, this index is trivially equal to zero. The distribution of the index is centered around 0, with a slight positive tail; however, the overall values remain far from the 0.5 threshold typically associated with spatial autocorrelation.

Table 1: Summary statistics

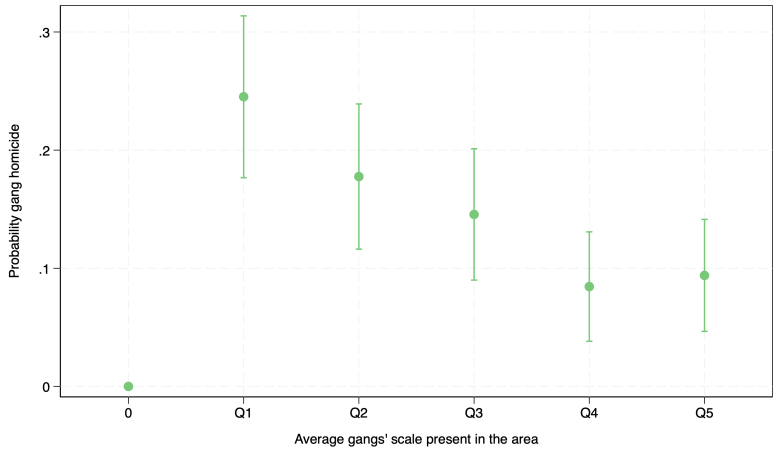
	Mean	SD	Min	Max	N
Panel A: gangs					
Presence	0.72	0.45	0	1	736
Number gangs	3	12.81	0	134	736
Max scale	4.38	2.231	1	9	528
Mean scale	3.29	1.64	1	7	528
Panel B: violence					
Fight	0.06	0.23	0	1	736
Number attempted homicides	0.82	7.94	0	156	736
Number homicides	0.41	2.26	0	36	736
Number gang homicides	0.24	1.57	0	28	736
Panel C: enforcement activity					
Arrests for drugs	206.90	1,918.97	0	21,180	736
Arrests local police	15.13	217.46	0	5,340	736
Number cocaine seizures	5.04	23.01	0	239	736
Number heroin seizures	1.03	7.81	0	105	736
Number marijuana seizures	10.45	50.09	0	546	736
Panel D: drugs					
Quantity seized cocaine (kg)	2.44	20.72	0	490.06	736
Quantity seized marijuana (kg)	27.56	324.42	0	8,435.65	736
Quantity seized heroin (kg)	1.14	17.83	0	466.86	736
Retail price cocaine (euro)	77.81	10.50	67.50	95	736
Retail price heroin (euro)	63.75	9.928314	45	75	736
Retail price marijuana (euro)	11.19	2.09	9	15	736
Wholesale price cocaine (euro)	38.25	2.44	35	42	736
Wholesale price heroin (euro)	25.19	5.30	15	32	736
Wholesale price marijuana (euro)	2.59	0.54	2	3.60	736
Average quality cocaine (% pure substance)	63.25	13.98	25.06	84.50	40
Average quality heroin (% pure substance)	19.60	10.28	0.63	38	19
Average quality marijuana (% pure substance)	12.16	5.67	0.20	29.21	57

Notes: Table displays summary statistics for selected variables in the data. Each observation corresponds to an location – district within Naples city, city in the province – year. Panel A presents variables related to gangs presence. The number of observations in max scale and mean scale is lower because these variables are missing in locations/years with no gangs ($736 \times 0.72 \approx 528$). Panel B presents variables related to violence. Panel C to enforcement activity, and Panel D to drugs. Average quality is not observed in all the locations/years.

participating; the minimum number of gangs involved is, reassuringly, 2, while the maximum is 14. We do not observe any conflicts for a contested market in which neither of the two gangs was present at the time of the fight. Instead, in the majority of cases (80 out of 93), both gangs were active in the market for which they were fighting. Finally, most fights (72%) last only one year, resulting in an average fight duration of 1.49 years.

3.2 Gang size and violence

In Figure 1, we presents the average probability of gang homicide along with the 95% confidence interval for areas with no gangs (0) and separately for the five quintiles of the distribution of the average gang scale in the area. As expected, the probability of gang homicide is exactly zero in areas with no active gangs. The probability of gang homicides is very high, reaching up to approximately 25%, in areas where only very small active gangs are present (Q1). Interestingly, as the average scale of active gangs rises, the probability of gang homicide gradually decreases, reaching its lowest point at 10% in the fifth quintile of the distribution. In other words, there is a 15% difference in the probability of gang homicide between areas with very small gangs and those with large active gangs. This suggests that the size of the active gangs in an area may have a potential negative relationship with the level of violence generated in that area. When looking at all homicides in Figure A7 conclusions are identical. Results are consistent when looking at the maximum gang scale in the area, instead of the average, for both gang homicides Figure A8 and all homicides Figure A9. To conclude, conclusions are unchanged also when considering the probability of fights in the area in Figure A10 and Figure A11, a direct action of gangs, rather than a general measure of violence.



Notes: This figure presents the average probability of gang homicides for locations-years with no gangs, and for the five quintiles of the average of scale of gangs present in the area distribution. An homicide is coded as gang homicide if there was any gang mentioning on the internet related to the homicide. The scale of a gang, in a given year, is the number of locations in which it is present.

Figure 1: Prob. gang homicide by average scale

Are larger gangs less violent? The previous descriptive evidence suggests that areas with larger gangs experience lower levels of violence. Moreover, by simply counting the number of fights

for each gang in each year, large gangs are 14% less likely to be involved in a fight.[6] However, without additional evidence, it is difficult to attribute this finding to gang behavior rather than to differences across areas and systematic selection regarding gang presence.

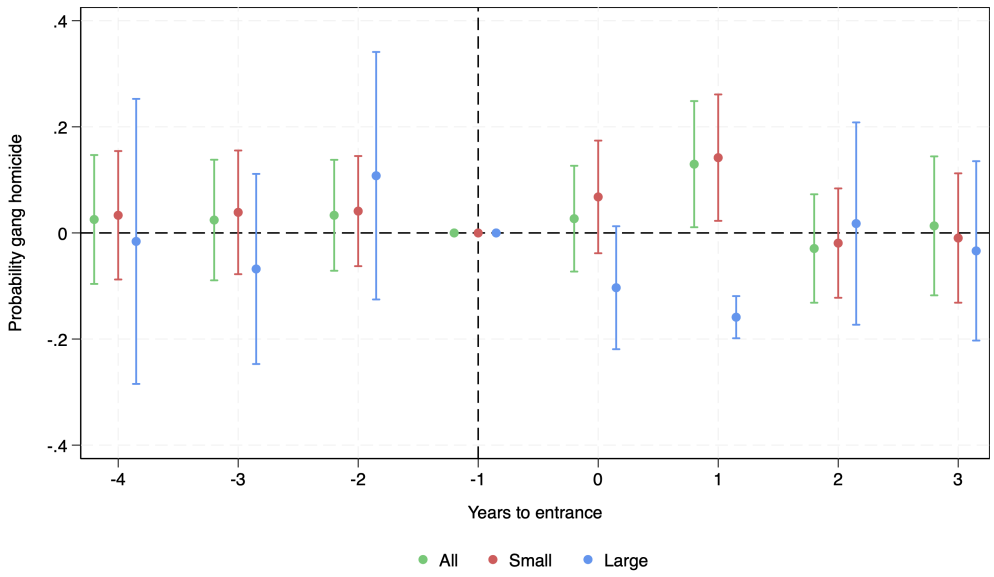
A first step is to account for unobserved differences across areas and years. Table A2 presents the correlations between various measures of violence (probability of homicide, probability gang homicide, probability of fight, number of homicides, number of homicides per capita, number of gang homicides per capita) and the average scale of active gangs. In columns 1, 3, 5 we control for both area and year fixed effects. Consistent with previous findings, all measures indicate that an increase in average gang scale is associated with a decrease in violence. Specifically, a one unit increase in average gang scale–with respect to an average of 1–is associated with a 10% reduction in the probability of homicide, 6% reduction in the probability of gang homicide, 36% decrease in the probability of fight, 18% decline in the total number of homicides, 36% reduction in the number of homicides per capita, and 30% in the number of gang homicides per capita. The results remain quantitatively similar when controlling for the number of active gangs in the area in columns 2,4, and 6. Consequently, our descriptive evidence cannot be explained by fixed characteristics of the areas and years or systematic sorting in the number of gangs.

3.3 Impacts of gangs' entry

To better understand the factors driving this correlation, we need to focus on the residual variation in the average scale of gangs after controlling for area and year fixed effects. This variation can arise from two scenarios: gangs entering or exiting the area. We focus on entry and explore the heterogeneous effects of gang entry on violence. To do so, we estimate an event-study design. To prevent contamination from later entries, we restrict our analysis to the last entry in the area. To explore the heterogeneity of gang entry, we will estimate the event study separately for generic entries, entries of small gangs (with a scale of 3 or lower), and entries of large gangs (with a scale greater than 3).

Figure 2 displays the event-study graph for three different models: generic entry (in green), entry of a small gang (in red), and entry of a large gang (in blue) on the probability of gang homicides. Consistent with expectations, the entry of a new gang into an area disrupts the equilibrium, leading to an increase in violence. Specifically, the entry of a new gang is associated with an approximately 16% increase in the probability of homicide in the area during the first period, compared to the omitted category, and a 75% increase in the second period. After two years, this

[6] Notice that large gangs are present, by definition, in more areas. This is associated with an higher number of fighting possibilities, which makes this figure even more striking.



Notes: This figure presents the event-study coefficients separately for the last entry of a new gang in the area, the last entry of a small gang, and the last entry of a large gang, on the probability of gang homicide. An homicide is coded as gang homicide if there was any gang mentioning on the internet related to the homicide. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. A gang is defined to entry in an area at time t if is present in the area at t, but not in $t-1$. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown. Standard errors clustered at the location level (district within Naples, city in the province).

Figure 2: Event study - probability gang homicide

effect gradually declines toward zero. This average effect conceals substantial heterogeneity based on gang size. Notably, the increase is more pronounced when a small gang enters the area, with increases of approximately 53% and 108% in the first and second periods, respectively. Conversely, the entry of a large gang is associated with a decrease in the probability of homicide, approximately -8% and -13% compared to the reference category. In both cases, these effects dissipate two years after entry.

The absence of pre-trends–though there appears to be a slight pre-trend in the model for large gang entry, more on this follows–is reassuring about the strength of the parallel trend assumption. Figure A12 shows the "raw data" version of the event study shown in Figure 2. In particular, we plot the average probability of gang homicide in the different years with respect to the entry of a gang, small gang, and large gang. As expected, results are in line with the event-study approach. However, given that here we don't have a reference category, we can dig deeper on the subtle pre-trend for large gangs. This is composed by two factors: a slight increase in probability of gang homicide in -2 and a decrease in the reference category (-1).

Figure A13 shows the variation in entry years used for the estimation. Entry involving both

type of gangs is widely dispersed across the sample. Figure A14 shows the same variation using the first–rather than the last–entry in the area. Figure A15 and Figure A16 replicate for the probability of homicide, rather than gang homicide, both the event-study and the graph with raw data. Figure A17 replicates with city and year fixed effects, and Figure A18 for the first entry in the area. Figure A19 replicates for the number of gang homicides, Figure A20 for the number of homicides, Figure A21 for the number of gang homicides per capita, Figure A22 for the probability of fight in the area.

It is possible that unobserved factors within a given year could simultaneously influence both gang entry and violence levels in an area, potentially with heterogeneous effects by gang scale. Entry is an endogenous decision made by gangs. To further strength the claim about the relationship between gang size and violence, we should exploit a set of exogenous entries. We do so by using entry predicted by a shift-share IV, rather than the true ones. We follow a two step approach:

$$\text{1 step:} \quad E_{ytj} = \eta \text{Exit}_{yt} \times \text{Distance}_{jyt-1} + \mu_t + \mu_y + \mu_j + u_{ytj}$$

$$\text{2 step:} \quad V_{yt} = \alpha + \sum_{l=-4}^{-2} \beta_j 1[t = \hat{E}_y - l] + \sum_{k=0}^{3} \beta_k 1[t = \hat{E}_y + k] + \epsilon_{yt}$$

In the first step, we predict gang entry using the shift-share IV. The shift is the exit of a gang from the same area that was not involved in any fight in the previous period. This allows us to consider exits due to reasons other than fights–such as enforcement activity–which could otherwise reintroduce endogeneity. The share is the distance of the gang from that area in the previous period. The logic behind this IV is straightforward: a gang's exit creates entry opportunities for others, especially for gangs that were already operating nearby. Table A3 shows the results of the first step. In the second step, we use these predicted entries, rather than actual entries, in our event-study analysis. As before, we estimate separate event studies for general predicted entry, predicted entry of small gangs, and predicted entry of large gangs. Figure A23 presents this robustness version of Figure 2. The two figures are very similar, although standard errors are significantly larger. This was expected, given the two-stage procedure. Nevertheless, conclusions from the graphs remain the same: we observe an increase in the probability of gang homicide after the entry of small gangs, and a decrease in this probability after the entry of a large gang. Figure A24 replicates the analysis with area and year fixed effects; results are unchanged, although there is a further increase in the standard errors which makes the decrease not statistically different from zero.

Although it is still possible that unobserved factors confound the previous estimates, the

presented evidence–from raw data to event studies and the event study combined with an IV–strongly suggests that larger gangs may behave differently from smaller ones. In particular, larger gangs appear to be less violent.

4 The retail drug market

In the previous section, we provided evidence supporting the idea that larger gangs tend to be less violent. To understand why this is the case and to study the relationship between market concentration and violence, we explore gangs' incentives for fighting. In this section, we outline some key facts about the retail drug market and develop a quantitative fighting model.

We present three facts about this market. First, a negative correlation between violence and the average drug quantity seized, suggesting that consumers dislike violence. Second, larger gangs have a higher probability of winning fights. Third, fights involving large gangs seems to create more violence.

We then present a model of the retail drug market where gangs can engage in fights to shut down competitors' selling points. The model's key mechanisms are informed by the evidence presented in the first part of this section. Consumers decide where to buy drugs, considering transport costs and the level of violence in the area. Gangs maximize expected profits by deciding whether to engage in fights and against whom. When deciding whether to fight, gangs weigh the expected additional profits from gaining larger market share against reduced demand and increased police presence. Consistent with the evidence presented, we allow gangs of different sizes to have heterogeneous fighting abilities, which influence their probability of winning fights, and heterogeneous effects on demand and police reactions.

4.1 Three facts

Here we present three facts about the retail drug market, which will guide the structure of the quantitative model.

FACT 1: Consumer dislike violence.

Figure A25 presents the scatter plot between the average quantity seized[7] and the number

[7] This is the number of grams in each seizure. Focusing on this measure allows us to ignore seizure selection at this stage of the paper, while still providing some evidence on the quantity of drugs found in each seizure. We will address this in later sections.

of non-gang related homicides per capita, which allows us to exclude any potential relationship between gang violence and the drug market. The data shows a downward trend in quantity with increasing violence: areas with more non-gang homicides tend to have lower average quantities per seizure. Figure A26 presents the same scatter plot with gang related homicides, results are consistent. This suggests that consumers may negatively value violence, consistent with insights from Levitt and Venkatesh (2000). Figure A27 presents the scatter plot with the number of arrests by local police per capita. Consistent with drug consumption not being a major criminal violation in Italy,[8] we do not observe any apparent relationship between the average quantity of drugs seized and the number of arrests by local police. However, this second exercise should be interpreted with caution, given the potential correlation between arrests by local police and drug seizures, which could impact the selection of cases included in our sample for average drug quantity. Hence, consumers appear to dislike violence, but this does not seem to be the case for police presence.

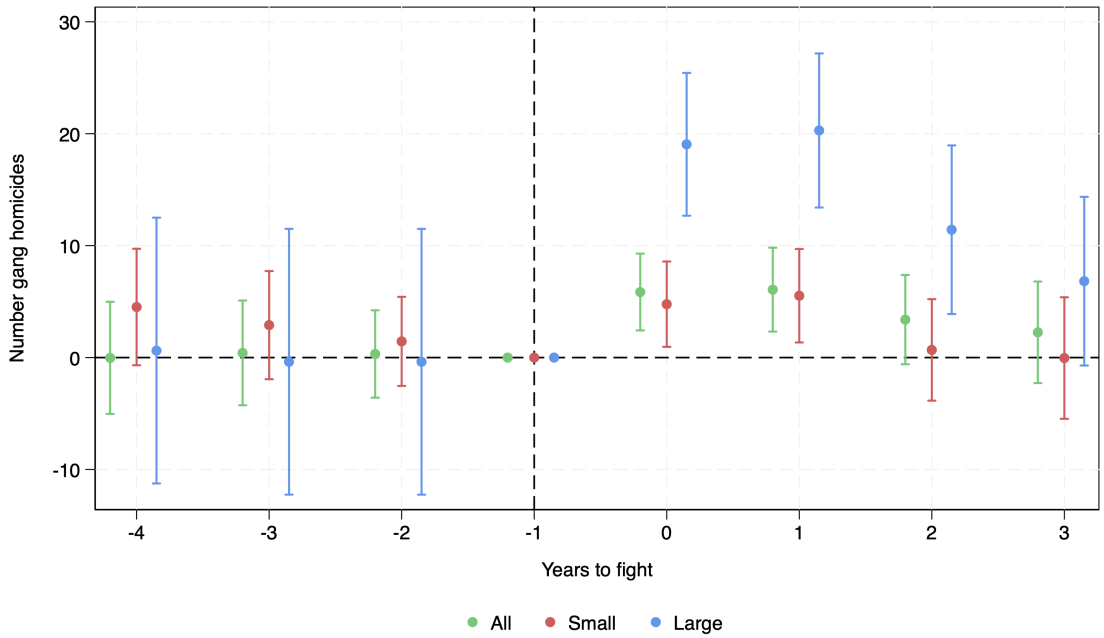
FACT 2: Larger gangs have a higher probability of winning fights.

Table A4 presents the differences in the probability of the fighting outcomes for large gangs compared to small gangs. This is calculted with a simple probit regression on the dummy variabile indicating the fighting outcome on a dummy variable that indicating the size of the gang. The sample is restricted to fights involving only two gangs (which accounts for 70 out of 100 fights). Perhaps unsurprisingly, large gangs have approximately three times the probability of winning fights compared to small ones. This increased probability is primarily driven by a reduced likelihood of draws, meaning that the fights have fewer inconclusive outcomes during the period under consideration. In other words, when engaging in a fight, a large gang is three times more likely to successfully push its competitor out of the area within the year.

FACT 3: Fights involving larger gangs create more violence.

Figure 3 shows how the number of gang homicides changes following the onset of fights in an area. At the outbreak of fights, consistent with the raw data presented in Appendix E, we ob-

[8]Under Italian law (Presidential Decree No. 309/1990, known as the Consolidated Law on Drugs), drug use itself is not a criminal offense, and possession for personal use is subject only to administrative sanctions such as suspension of driving licenses or firearms permits, rather than criminal penalties. For first-time offenders, administrative sanctions are typically not applied; instead, offenders receive a warning and a formal request to refrain from use (source: https://canestrinilex.com/en/readings/drug-offences-in-italy-detention-and-dealing).



Notes: This figure presents the event-study coefficients separately for the general first fight, the first fight involving only small gangs, and the first fight involving at least one large gang, on the number of gang homicides in the area. An homicide is coded as gang homicide if there was any gang mentioning on the internet related to the homicide. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown.

Figure 3: Event study - number of gang homicides

serve a spike in gang homicides. This effect persists for up to two years following the start of the fight. When we differentiate between fights involving only small gangs and those involving larger gangs, we observe that the effect is present in both cases; however, it is significantly larger when larger gangs are involved. Thus, fights involving larger gangs result in greater levels of violence, with no evidence of pre-trends in any of the models. Figure A28 presents the event study considering all homicides rather than only gang-related homicides. Figure A29 shows the variation in fighting years used for the estimation. Fights involving small gangs are widely dispersed across the sample, while those involving larger gangs are much less dispersed. Nevertheless, we still observe fights involving large gangs across different years. The pattern confirms that larger gangs generate more violence when fighting. This could occur for several reasons, ranging from greater firepower and manpower (which would also be consistent with their higher winning probability) to simply having more people to target during fights.

As a consequence of this increase in violence, we should expect an increase in police attention. This is exactly what we observe in figure A30 where we plot the event study on the number of

drug-related arrests. Conclusions are similar to the previous graph: at the onset of fights, the number of drug related arrests increases, but it does so significantly more when the fight involves at least one large gang. Figure A31 replicates on the number of arrests by the local police. Is this (heterogeneous) increase in police attention entirely driven by the heterogeneous increase in violence? Figures A32 and A33 replicate the arrests event studies controlling for the number of homicides in the area. Once controlled for this, the increase in police attention in the first two periods after the outbreak becomes very small, not statistically different from zero, and not statistically different between fights involving large an small gangs.

4.2 Potential mechanisms

The evidence presented highlights the importance of the heterogeneous impact on violence of fights involving gangs of different sizes. Although we treat this as a primitive in our model, it can be rationalized by greater firepower and/or more potential targets. In a dynamic framework, this increased violence could also be justified as an optimal deterrence strategy against future fights. However, explaining this difference falls outside the scope of this paper. As a consequence of this primitive, one can rationalize both the higher probability of winning fights and the stronger police reaction observed for larger gangs. This suggests three main potential mechanisms behind the negative correlation between gang size and violence.

First, a *deterrence* mechanism. Smaller gangs, recognizing their lower probability of winning fights against larger gangs, may choose to avoid confrontation. This leads to a lower probability of larger gangs being involved in fights for a passive reason: fewer fights are actually initiated against them.

Second, a *demand* mechanism. As suggested by Fact 1, consumers dislike violence. As a result, fights involving larger gangs create more market disruption. Gangs may anticipate this stronger negative effect on demand and limit this destructive behavior.

Third, a *self-regulation* mechanism. Increased violence is followed by a strong police reaction, which is clearly costly for criminal organizations. In other words, implementing this violent behavior is more costly for larger organizations, since they attract greater regulatory attention, consistent with insights from the self-regulation literature (e.g., Erfle & McMillan, 1990).

To test these potential mechanisms and perform policy counterfactuals, we develop a quantitative fighting model.

4.3 Model - Setup

The economy consists of a finite set of areas (indexed $y = 1, 2, \ldots, Y$) and features a discrete number of gangs $j = 1, 2, \ldots, J$, and consumers $i = 1, 2, \ldots, I$, of different drugs $v = 1, 2, \ldots, V$ over various periods $t = 1, 2, \ldots, T$.

Gangs Gangs are heterogeneous in their initial scale and, consequently, in their fighting probabilities and the violence generated. They strategically decide whether to fight and whom to target. If successful, they displace competitors from the area. In this decision-making process, gangs weigh the expected additional profits from gaining larger market share against the costs arising from decreased demand due to heightened violence. In the benchmark model, gangs are price and quality takers (meaning they produce drugs at a given price and with a homogeneous production function). This assumption simplifies the benchmark model and highlights the key mechanisms at work.

Police Police is essentially a function that, given the fighting matrix of the period, allocates attention across the different areas.

Consumers Consumers have homogeneous preferences and decide where to buy drugs and from which gang, essentially choosing a bundle (j, y). The outside option is not to buy any drug. There is a fixed number of consumers for each type of drug, estimated using population data and consumption propensity (more information in D). When choosing where to purchase drugs, geographically dispersed consumers weigh transportation costs against violence in the area, along with a set of unobserved preferences. Demand follows a simple nested logit structure, similar to Goldberg, 1995, where the nests represent geographical areas.

Time The model is static, which is justified by the need to maintain tractability in computing an equilibrium with many gangs and locations. Consequently, in each period, gangs observe their exogenous starting scale, reconstructed from the data, and make optimal decisions based on it.

Space Although in reality gangs might operate more than one dealing point in each area, we assume that they can have at most one point in each market, an assumption similar to most of the literature on spatial competition in retail sectors, e.g. Aguirregabiria & Vicentini, 2016. Denote by $\mathcal{Y}_{jt} = \{y \mid y_{jt} = 1\}$ the set of areas in which gang j is active at time t. Define the matrix $\mathbf{Y}_t$ where $y_{yj} = 1$ if gang j has a dealing point in y at t. Given the absence of fixed costs associated

with entering different types of drug markets, we can safely assume that, on the extensive margin, if a gang is present in an area, it can produce all types of drugs.[9] This significantly simplifies the state space, as we need to consider only one network matrix per period instead of V matrices. That being said, if selling a specific drug in an area is not profitable, the gang can always adjust on the intensive margin and set the quantity to zero.

4.4 Model - Demand

Utility Consumer i, living in area y_i, of drug v, at time t, decide whether to buy drugs from gang j in area y, or the outside option of not to buy any drugs $y = 0$. The conditional indirect utility that consumer i receives from buying drugs v from j in y is:

$$u_{ijyvt} = \alpha_v p_{vt} + \mu_{vm} F_{ytm} + \xi_y + \xi_v + \xi_t + \xi_{yvt} + d_v g_{iy} + \epsilon_{ijvt} + (1-\rho)\epsilon_{iyvt} \quad (1)$$

where p_{vt} is the average price charged for drug v at t, $\xi_y, \xi_v, \xi_t, \xi_{yvt}$ are unobserved, to the econometrician, but observed by suppliers and consumers, preferences for the drug v, supplied in area y, at time t. g_{iy} is the distance between the areas. F_{ytm} indicates the presence of a fight between gangs of scale m in the area. Hence, in line with fact 1, we allow consumers to have preferences over violence–μ_{vm}–potentially varying heterogeneously with the scale of the gangs involved in the fight, consistent with fact 3. If this parameter is negative, as suggested by the preliminary evidence presented in section 4.1, it generates a cost of fights for gangs. Additionally, if this parameter is larger for fights involving large gangs, then it creates a heterogeneous impact on the retail market. ϵ_{ijvt} are consumer specific taste shocks for drug v supplied by j in t, and, similarly, ϵ_{iyvt} are consumer specific taste shocks for drug v in y in t. We assume that both shocks are standard type-I extreme value distributed.

Define the nests to be $g = 0, 1, ...Y \ \forall v$ where $g = 0$ denotes the outside option (assume $g_{i0} = 0 \ \forall i$), and its other values are the different areas in the province of Naples. Therefore, parameter ρ, the nesting parameter, governs the switching between the areas. We impose perfect substuitability across nests ($\rho = 0$). Notice that, in this framework, consumers are not allowed to switch type of drugs. As standard in the literature, denote by $\delta_{jyvt} = \alpha_v p_{vt} + \mu_{vm} F_{ytm} + \xi_y + \xi_v + \xi_t + \xi_{yvt}$ the mean consumer valuation. Given that the demand process is identical for

[9] This assumption is justified by observations that all drugs are seized in the areas. Figures A34 and A35 show that areas with cocaine seizures typically also see seizures of the other two drugs. Therefore, we do not observe specialization in drug trafficking by area, but rather a scenario in which all drugs are sold in the same area, consistent with our assumption.

each period, from now on we will omit the time subscript.

Consumer problem Define $d_{(y,j)}$ to be the indicator of the consumer decision; $d_{(y,j)} = 1$ if the consumer chooses the bundle (y, j) and 0 otherwise. The consumer problem may be written in the following way:

$$\begin{aligned} \max_{d_{(y,j)}} \sum_{(y,j)} d_{(y,j)} u_{ijyv} \quad & \forall v, t \\ \text{s.t.} \sum_{(y,j)} d_{(y,j)} = 1 & \end{aligned}$$

Since in this model an individual is defined by product specific shocks $(\epsilon_{ijv}, \epsilon_{iyv})$ and by its location y_i, this implictly defines the set of individual attributes that lead to the purchase of good (j, y) from y_i. For ease of exposition, we can think about this problem as if it was composed by two steps. First, the across nest decision, where the consumers choose where to buy drugs. Second, the within nest decision, where consumers choose from which gang to buy drugs.

Within nests The within nest decision problem is fairly simple. Given the consumer specific taste shock, the consumer chooses the gang in the area which maximize its utility. Given that the only difference between consumers is their location, and in this problem they have already chosen the optimal area, the share of consumers choosing a specific gang will not depend on i. Appendix A.1 provides the conditional demand at its complete derivation.

Across nests In the across nests decision, geographically dispersed consumers weight unobserved preferences, trasportation costs, and disutility from police presence. By exploiting the properties of the standard type-I extreme value distributed consumer specific taste shock ϵ_{iyv}, we derive the across nests demand function (please refer to appendix A.1 for additional details).

Consumer sorting across locations plays a key role in demand estimation, given the nature of the data. We use consumer sorting across, rather than within, nests to estimate demand parameters. To do so, we need to bring these unconditional demand for nests in an reduced form model we can estimate in the data. By writing the unconditional demand for drugs in nest y as weighted sum of the conditional demands, taking the logarithm of these shares, and exploiting the properties of the logarithm (appendix A.1 shows steps), we can rewrite these uncondtional demand functions in a log-lin form:

$$log(s_{yvt}) = \alpha_v p_{vt} + \mu_{vm} F_{ytm} + f_t + f_y + f_v + \xi_{yvt} \tag{2}$$

which we then can bring directly to the data for demand estimation.

Unconditional demand By combining the conditional demand within nests, with the across nest demand, we obtain the unconditional demand for the bundle (y, j) (please refer to appendix A.1).

4.5 Model - Supply

Production Gangs produce drugs using pure drug r and cutting substances s according to a Leontief production function:

$$q_{jyvt} = min\{\frac{s_{jyvt}}{1 - x_v}, \frac{r_{jyvt}}{x_v}\} \tag{3}$$

x_v is the inverse of the average percentage of pure drug in the dose, and it estimated from the data. This production function is very intuitive: to produce $q_{jyvt} = 1$ gram of drug, the gang needs x_v grams of pure substance and $1 - x_v$ grams of cutting substance. Profits from dealing point y and drug v are: $p_{vt}q_{jyvt} - k_{vt}s_{jyvt} - c_{vt}r_{jyvt}$.

Firm problem Gangs solve a two-stage game:

1. In the first stage they decide whether, where, and against whom to fight. In other words, they choose the optimal fighting matrix $\mathbf{F}_{jt}$. The combination of these matrices, and the realization of the fighting outcomes will determine the network matrix of the period $\mathbf{Y}_t$;

2. Given fighting outcomes, demand and police attention, profits are realized.

Second stage Given that gangs in the benchmark model are price and quality takers, in the second stage profits are simply realized given fighting outcomes and demand. Writing profits with an implicit demand function:

$$\Pi(\mathbf{Y}_t, \mathbf{F}_t) = \sum_{y \in \mathcal{Y}_{jvt}} \sum_{v} [p_{vt}q_{jyvt}(\mathbf{F}_t) - q_{jyvt}(\mathbf{F}_t)[k_{vt} + (c_{vt} - k_{vt})x_v]] - \delta O_{yt} \tag{4}$$

where O_{yt} is the police attention in the area. Hence, δ captures the costs deriving from police enforcement, which can be rationalized with arrests, drug seizures, and/or other potential costs.

Police reaction As mentioned previously police is essentially a function, the *police reaction function*:

$$O_{yt} = \bar{o}_y + f(\lambda_m \mathbf{F}_{jty}) \tag{5}$$

where $\bar{o}_y$ is the average police attention in y, $\mathbf{F}_{jty}$ is the matrix of fights of gang j in y at t. Consistently with fact 3, we allow for an heterogeneous impact of fights on police attention λ_m, due to the different amount of violence these fights generate. If police attention increases more with fights involving larger gangs, as suggested by the evidence presented in Section 4.1, this creates an additional cost of fighting for larger gangs. When fighting, they generate a stronger police response – the regulator. Therefore, in equilibrium, we may observe lower fighting propensity, since larger gangs anticipate this increased cost.

Fighting game The core part of the model is the fighting game. In this game, gangs must decide whether to fight, against whom to fight, and for which area. The choice set of the game is $\mathcal{F}_{jt} = \{(y, o) = 0, 1 : \forall (y, o) \in \mathcal{Y}_{jt} \times \mathcal{J} - j\}$, where $\mathcal{Y}_{jt} = \{y \mid y_{jt} = 1\}$ is the set of areas in which gang j is active at time t. In other words, we restrict gangs to fight only for areas in which they are present in the period (which accounts for 86% of fights in the data). This assumption substantially reduces the dimensionality of the choice space. We do not restrict the number of fights a gang can engage in during one period. However, we do not model any interaction between fights within the period. In other words, as will become clear when discussing the fighting mechanism, the probability of a gang winning a fight is independent of the number of fights in which the gang is involved in the period. While we acknowledge this assumption is problematic, it allows us to avoid strategic interaction among gangs which would substantially complicate the game. Moreover, it enables us to treat fights among multiple gangs (which represent approximately 40% of fights in the sample) as independent fights between single gangs. Finally, we allow fights to end with either a definitive outcome (one gang wins and the other loses) or in a draw. This allows us to accommodate fights lasting more than one period as repeated fights with draws. The choice set can be represed by the set of $JY \times JY$ matrices $\{\mathbf{F}_{jt} \ \forall j, t\}$ where $f_{yo} = 1$ if gang j at time t decide to fight against gang o for y. With this notation, we are implictly setting $f_{yo} = 0 \ \forall y \notin \mathcal{Y}_{jt}$, and, clearly $f_{yj} = 0$ always. Given the similarity between this fighting game and a classical static entry model, following Reiss & Bresnahan, 1990, Berry, 1992, and Mazzeo, 2002, we do not consider mixed strategy equilibria.

Gang profits Throughout this subsection, we will compare gangs profits–determined in the second stage of the game–across different possible gangs fighting decisions and states of the world.

To easy exposition, let's define an implicit profit function:

$$\Pi(\boldsymbol{\Upsilon}, \boldsymbol{\omega}) = \pi^* : \mathbb{R}^Y \times \Omega^{YJJ \times YJJ} \to \mathbb{R}$$

where $\boldsymbol{\Upsilon} = [\mathbf{x}, \mathbf{p}, \mathbf{c}, \mathbf{k}, \boldsymbol{\mu}, \boldsymbol{\alpha}, \boldsymbol{\xi}]$ is the vector of exogenous profit shifters, and $\boldsymbol{\omega}$ is the matrix of possible possible states of the world with elements:

$$\omega_{yjo} \in \Omega = \{\text{WNF,WF,P,D,NF,L}\}$$

which indicate, respectively, win without fighting, win with fighting, peace, draw, non fight, and loose. Let's define a fighting outcome function:

$$P(\mathbf{m}, \mathbf{F}, \omega) = p : [0,1]^{J \times T \times Y \times J} \times \mathbb{R}^J \times \Omega \to \mathbb{R}$$

which, for each set of gang scale, fighting decisions, and possible state reports the probability of that state happening. Then, gang j solve:

$$V(\boldsymbol{\Upsilon}, \mathbf{F}_{-j}) = \max_{\mathbf{F}_j} \sum_{\omega \in \Omega} P(\mathbf{m}, \mathbf{F}_j, \mathbf{F}_{-j}, \omega) \Pi(\boldsymbol{\Upsilon}, \mathbf{F}_j, \mathbf{F}_{-j}, \omega) - \gamma \mathbf{F}_j \tag{6}$$

where $\gamma \sim N(\gamma, \sigma_\gamma)$ is a random fixed cost from fighting.

The rest of this subsection is structured as follows: (i) we discuss the fighting mechanism; (ii) we present a simplifyied two gangs game; (iii) we extend this simple game to the multi-gang context; (iv) we show how police reacts to violence and how violence is determined.

Fighting mechanism Building on the seminal paper by Donohue and Levitt (1998), each gang j is characterized by a fighting ability ϕ_{jt}, composed by an observed fighting ability ϕ_j, common knowledge among all gangs, and an unobserved (to everyone) shock ϵ_{jt}. This unobservable component can be thought of as randomness in the fight outcomes. The ϵ's are assumed to be independently and identically ETV1 distributed with location 0 and scale σ_ϵ. Hence, σ_ϵ measures the unpredictability of the fighting outcome. Notice that, consistently with fact 2, we allow the fighting ability–and therefore the fighting outcome probability–to be heterogeneous across gangs, and hence gangs' scale. Given that the observable fighting ability is observed by all the players, as all the other components of profits, this is a game of complete information. One can in principle allow for incomplete information by making the fighting ability private information.

Suppose a fight between a gang j and o at time t. Fighting mechanism is a step function:

$$\begin{cases} \phi_j + \epsilon_{jt} - \phi_o - \epsilon_{ot} > \Phi & j \text{ wins} \\ \Phi \geq \phi_j + \epsilon_{jt} - \phi_o - \epsilon_{ot} > -\Phi & \text{draw} \\ -\Phi \geq \phi_j + \epsilon_{jt} - \phi_o - \epsilon_{ot} & j \text{ loses} \end{cases} \tag{7}$$

where Φ is the step parameter. As mentioned before, here there is no mention of other fights. In other words, the fighting ability, and therefore the probability of the different fighting outcomes is independent from the number of other fights. This is an important assumption which simplifies substantially the transition from the two gangs game to the multi-gang one, since it allows us to treat fights as independent, and abstract from coalitions.

A simple fighting game For simplicity, we start with a simple fighting game between two gangs j and o in an area y. In this simplified game, we compare the following set of profits:

$$\{\Pi(\boldsymbol{\Upsilon}, WNF) = \pi_{WNF}; \Pi(\boldsymbol{\Upsilon}, WF) - \gamma = \pi_{WF}; \Pi(\boldsymbol{\Upsilon}, P) = \pi_P; \Pi(\boldsymbol{\Upsilon}, D) - \gamma = \pi_D; \Pi(\boldsymbol{\Upsilon}, NF) = \pi_{NF}; \Pi(\boldsymbol{\Upsilon}, L) - \gamma = \pi_L\}$$

Each year t is divided in three periods. In period t0, before the actual start of the game, all gangs learn about the observable fighting ability of all the others. Then, in period t1, they play the sequencial fighting game. Once a set of optimal fighiting matrices is determined, in period t2 shocks are revealed and fighting outcomes realized. Therefore, at period t2, the new network matrix of the period $\mathbf{Y}_t$ is determined. In period t3 profits are realized.

In period 1, the two gangs play a sequencial fighting game. Nature gives a random opportunity to fight to one of the gangs. The chosen gang can choose whether to fight (F) or not (NF). If NF is chosen, then they will get peace profits π_P. If, instead, F is chosen, it is the turn of the other gang, which can choose whether to fight back (F) or not (NF). If choose not to fight, then it exits the area, determining the win-non fight profit for j, π_{WNF}, and the non fight profit for o, π_{NF}. If instead, o chooses to respond, then both get the expected profit from fighting, $\mathbb{E}\pi_F = P(\phi_j + \epsilon_{jot} - \phi_o > \Phi)\pi_{WF} + P(\phi_j + \epsilon_{jot} - \phi_o < -\Phi)\pi_L + (1 - P(\phi_j + \epsilon_{jot} - \phi_o > \Phi) - P(\phi_j + \epsilon_{jot} - \phi_o < -\Phi))\pi_D$ for j, and similar by changing the probabilties and relevant profits for o. Given the sequencial nature of the game, the appropriate solution concept is the Subgame Perfect Nash Equilibrium (SPNE).

Before turning to the SPNE with uncertainty, let us examine the case of no uncertainty $\sigma_\epsilon = 0$. Appendix A.2 presents all the SPNEs for this game. In this case, we have six possible SPNEs, depending on parameter values and the distribution of second-stage profits. These six possible SPNEs map into three scenarios: (i) j exits, (ii) o exits, (iii) multiple equilibria. Specifically, j exits whenever o will win the fight, or they will draw but o can credibly sustain the threat of fighting. The opposite holds for the scenario in which o exits. Finally, we have multiple equilibria when they will draw and nobody can credibly threaten to fight (a scenario in which the first to get the opportunity to fight wins the area) or both can credibly threaten to fight (a scenario in which the first to get the opportunity to fight exits the area). Importantly, in all these scenarios, a unique outcome emerges: no fighting. This result is in line with the classical literature on conflict with no uncertainty.

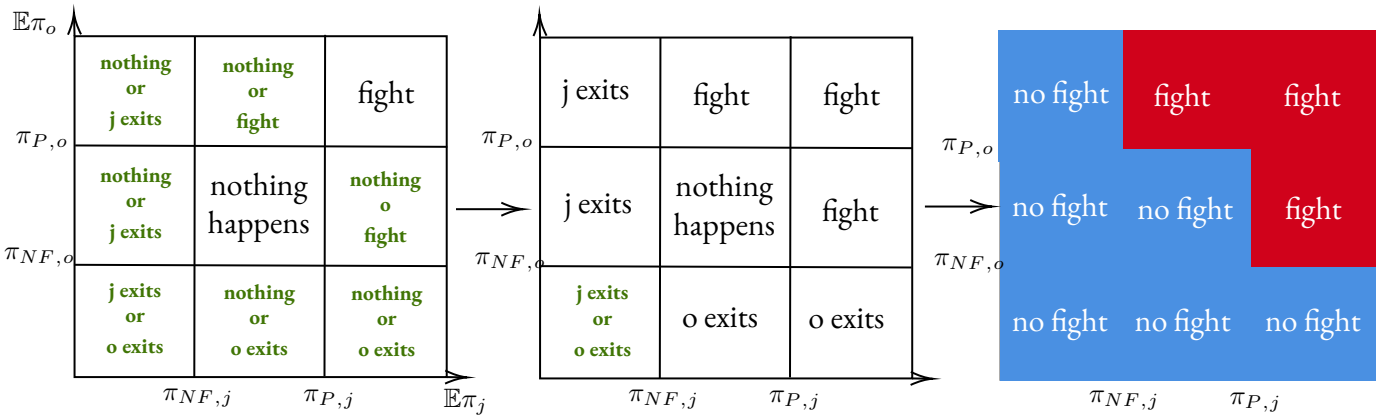


Figure 4: Fighting outcomes

In appendix A.3 we present SPNEs for the game with uncertainty. When we allow for $\sigma_\epsilon > 0$, nine SPNEs emerge. These are summarized in Figure 4. In many cases the actual equilibrium depends on nature choice, which generates a situation of multiple equilibria (bold green in Figure 4). To address this multiplicity, we select the equilibrium that would emerge as a self-absorbing state if this game were (non-strategically) repeatedly played.[10] These correspond to 5 possible scenarios: (i) j exits, (ii) o exits, (iii) multiple equilibria, (iv) nothing happens, (v) fight. Specifically, j exits whenever expected profits from fighting are lower than those from not fighting, and o can credibly threaten to fight. The opposite holds for the scenario in which o exits. Multiple equilib-

[10] For example, in the second case, if nature chooses gang j, then gang o would exit the market. If, instead, gang o were chosen, nothing happens. Now, suppose this game is played repeatedly. Eventually, gang j will be chosen by nature, which will cause o to exit the market, creating a self-absorbing equilibrium.

ria appear when expected profits from fighting are lower than those from not fighting for both gangs. In this case, no gang can credibly threaten to fight, and whoever gets the first opportunity to fight wins the area. Scenario (iv) occurs–nothing happens–when expected profits are higher than profits from not fighting for both gangs, but never higher than profits from peace. In this case, both gangs can credibly threaten to fight, so neither chooses to fight. Finally, a fight happens whenever both gangs have incentive to fight as long as the other fights (expected profits higher than profits from not fighting), and at least one of them has expected profits from fighting higher than peace profits. In this case both gangs can credibly threaten to fight, and given that fighting is optimal for at least one of them, eventually a fight will occur. So, with uncertainty, two outcomes may occur, depending on the profit distribution: fighting and not fighting. In other words, some degree of uncertainty is necessary to sustain a fighting equilibrium.

To shed light on the probability of the fighting outcome happening, let's dig deeper into the choice probabilities predicted by the model. The choice probabilities predicted by the model are:

$$
\begin{cases}
Pr(NF,NF) = Pr(\pi_j^{NF} \leq E\pi_j \leq \pi_j^p \;\&\; \pi_o^{NF} \leq E\pi_o \leq \pi_o^p), \\
Pr(F,F) = Pr(\pi_j^{NF} \leq \pi_j^p \leq E\pi_j \;\&\; \pi_o^{NF} \leq E\pi_o \leq \pi_o^p; \\
\qquad \pi_j^{NF} \leq E\pi_j \leq \pi_j^p \;\&\; \pi_o^{NF} \leq \pi_o^p \leq E\pi_o; \pi_j^{NF} \leq \pi_j^p \leq E\pi_j \;\&\; \pi_o^{NF} \leq \pi_o^p \leq E\pi_o), \\
Pr(NF,F) = Pr(E\pi_j \leq \pi_j^{NF} \leq \pi_j^p \;\&\; \pi_o^{NF} \leq E\pi_o \leq \pi_o^p; E\pi_j \leq \pi_j^{NF} \leq \pi_j^p \;\&\; \pi_o^{NF} \leq \pi_o^p \leq E\pi_o) + \\
\qquad \int T(NF,F) 1[(E\pi_j, E\pi_o) \in R] dF_{E\pi_j, E\pi_o}, \\
Pr(F,NF) = Pr(\pi_j^{NF} \leq E\pi_j \leq \pi_j^p \;\&\; E\pi_o \leq \pi_o^{NF} \leq \pi_o^p; \pi_j^{NF} \leq \pi_j^p \leq E\pi_j \;\&\; E\pi_o \leq \pi_o^{NF} \leq \pi_o^p) + \\
\qquad \int (1 - T(NF,F)) 1[(E\pi_j, E\pi_o) \in R] dF_{E\pi_j, E\pi_o}
\end{cases}
$$

where

$$R = \{E\pi_j, E\pi_o | E\pi_j \leq \pi_j^{NF} \leq \pi_j^p \;\&\; E\pi_o \leq \pi_o^{NF} \leq \pi_o^p\}$$

The first two equalities in 4.5 are simple. For example, the model predicts *(NF,NF)* uniquely if and only if the expected profits belong to the central quadrant. Equalities three and four are more complicated. Both probabilities consists of the case when *(NF,F)*, or *(F,NF)*, are the unique equilibrium of the game (top left quadrants and bottom right ones), and olso when *(NF,F)*, or *(F,NF)*, are a *potentially observable outcome* of the game and it is the outcome that was "selected". Following Ciliberto & Tamer, 2009, define $T(NF, F)$ the selection mechanism function. This function "splits" the ME quadrant in the two possible equilibrium, determining the choice probabilities. The problem is that this function is unknown to the econometrician, and can potentially be different over gangs, areas, and time. In other words, if we were interested in the composition of the market, this simple fighting game would have multiple equilbria.

However, we are not interested in the composition of the market, but only in whether a fight occurs or not, and this outcome is predicted uniquely by the model; this argument is very similar to the insight on the prediction in the *number*, rather than the identity, of entrants by Reiss and Bresnahan (1990) and Berry (1992). This is clear if one looks at the second matrix of figure 4. Outcome probabilities predicted by the model are summarized in section A.4. Given uniqueness of the second stage equilibrium, the model predicts *uniquely* whether a fight is going to happen or not, conditional on the observables and parameters. In other words, the fighting game has a unique equilibrium in the fighting outcome, which is what we are interested in.

This paper investigates how market structure determine fights in the retail drug market. In particular, we are interested in how the fighting propensity changes with the scale of gangs in the area. Given the derived outcome probabilities, this translates into: $\frac{\triangledown Pr(F_{jo}=1)}{\triangledown m_j}$. Theoretically, what is the sign of this derivative? Computing this derivative explicitly is a challenging exercise. However, we can achieve the same result by exploring how the outcome changes in the expected profit space. We do so in Figure A37. Consider starting from a non-fighting equilibrium, as in panel A. Suppose now that, all else remaining constant, we counterfactually increase gang j's scale. This has five distinct consequences on the model's primitives. Let us examine their effects on the fighting probability separately. The first obvious consequence is an increase in the probability of winning the fight, which increases j's expected profits from fighting. As shown in Figure A37 B, this can lead to a switch into fighting equilibrium. Second, the decreased probability of the opponent winning the fight reduces their expected profits from fighting (*deterrence* effect), which could again lead to a switch in the equilibrium (panel C). Third, by being active in multiple areas, higher scale ensures revenue diversification, which increases the expected profits from fighting (panel D). Fourth, if disruption generated by large gangs is higher, and consumers dislike fights (as suggested by facts 1 and 3), higher scale implies lower expected profits from fighting (panel E), which could again switch the equilibrium (*demand*). To conclude, if fights of larger gangs generate a stronger response of the regulator (as suggested by fact 3), higher scale implies lower expected profits from fighting (panel F). Taking these factors together, theoretically, the sign of the derivative we are interested in is a priori *ambiguous*, as it combines different mechanisms with opposing signs. Ultimately, it depends on the combination and strength of these mechanisms, and therefore on fighting probabilities and demand elasticities. Different parameter sets may yield different signs of the derivative. Therefore, to answer this research question, we must estimate these parameters and determine which sign emerges from the estimated parameter set. We will then counterfactually vary parameter values to study how different mechanisms

contribute to the sign of this derivative.

The extended game We now extend back our game to a multi-gang and multi-area setting. We can think about this extended fighting game as a collection of *connected* 2 gangs 1 area games. They are connected because decisions in one simple game has consequences on the optimal decisions of the others. The existence of multiple equilibria in the extended game is not an estimation issue in this paper. Nevertheless, it may still be an undesirable feature when turning to simulations and results. Characterizing all the equilibria may be very computational intensive, and iterative procedures may converge to one possible equilibrium, with impossibility of discussing general implications for all the possible equilbria.

Hence, we need to study the sources of multiplicity. Consider the 2-1 game between j and o in y. We are interested in the sign of $\frac{\nabla Pr(F_{joy}=1)}{\nabla F_{j'o'y'}}$. If these derivatives would be all equal to zeros, then we would have a single equilibrium. Unfortunately, this is not the case. Given our assumptions on the absence of strategic interactions in fighting decisions (no economy/diseconomy of scale in the number of fights), the only connection between the simple 2-1 games is in the (expected) profits. Formally, $\frac{\nabla P(\mathbf{m},\mathbf{F}_j,\mathbf{F}_{-j},\omega)_{joy}}{\nabla F_{j'o'y'}} = 0$ but $\frac{\nabla \Pi(\mathbf{\Upsilon},\mathbf{F}_j,\mathbf{F}_{-j},\omega)_{joy}}{\nabla F_{j'o'y'}}$ potentially not. In particular, fights by other gangs and/or in other areas may generate changes in violence and the potential number of gangs in the areas, thereby modifying consumer decisions, profits in all possible states, and consequently fighting incentives. Therefore, the extended game has multiple equilibria. In our simulation, we will characterize equilibria determined by no-fight in the other connected 2-1 games.

4.6 Equilibrium

The model can be summarized in the following three vectors:

- Parameters: $[p_{vt}, c_{vt}, k_{vt}, \alpha_v, d_v, \mu_{vm}, \xi_y, \xi_t, \xi_v, x_v, \lambda_m, \bar{o}_y, \gamma, \delta, \phi_m, \sigma_\epsilon, \Phi]$
- State variables: $[Y_{jyt}; F(D_i, y_i); m_{jt}; g_{yy'}]$
- Choice matrices: $\mathbf{F}_{jt}$

And in the following equations:

$$\begin{cases} q_{jtvy} = d(p_{vt}; g_{yy'}; F_{myt}; \alpha_v; d_v; \mu_{vm}; \xi_y; \xi_t; \xi_v) & \text{demand} \\ O_{yt} = \bar{o}_y + p(\lambda_m; F_{myt}) & \text{police} \\ \pi_{jty} = \pi(q_{jtvy}; p_{vt}; x_v; k_v; c_v; \mathbf{Y}_t; O_{yt}; \delta) & \text{profits} \\ Pr(F_{ytjo}) = f(\Pi; \phi_b; \Phi; \sigma_\epsilon, \gamma) & \text{fighting decision} \\ Pr(W_{ytjo}, D_{ytjo}, L_{ytjo} | F_{vytj} = 1) = w(\phi_b; \Phi; \psi; \sigma_\epsilon) & \text{fighting outcomes} \\ \mathbf{Y}_t = y(\mathbf{Y}_{t-1}; W_{ytjo}; D_{ytjo}; L_{ytjo}; F_{vytj}) & \text{network determination} \end{cases}$$

An equilibrium is a matrix of fight choices $\mathbf{F}_{jt}$ such that, given parameters and state variables, this matrix is a Sub-game Perfect Nash Equilibrium of the fighting game (6).

5 Identification and Estimation

To quantify the strength of the different mechanisms contributing to the relationship between market structure and fighting probability, we structurally estimate the model.

Data Before turning to the details of identification and estimation, it is important to discuss briefly again the data to underline the bridge between the model and the data. Table A5 summarizes all the available data, the corresponding role in the model, and its source. We have data on the network matrices (both ex-ante and realized, since we can re-construct the ex-ante matrices by reverting the fights), observed average drug quality, prices, and fights decisions and outcomes. However, we do not directly observe drug quantities and police attention. We have some measures of these two unobserved variables, which are inherently selected, as discussed in detail in section 4.1. Hence, the final step is to *model* this selection.

Selection Drug quantity is unobserved ($q_{yvt} \to q^*_{yvt}$). Suppose the following selection equation:

$$Q_{vyt} = s(q^*_{vyt}, O^*_{yt}, \epsilon_{ytv}) = q^*_{vyt} s(O^*_{yt}, \epsilon_{ytv})$$

where O^*_{yt} is police attention and ϵ_{ijv} are other characteristics affecting seizure rates, potentially

correlated with demand and/or determinants of the market.

Police attention Police attention is unobserved ($O_{yt} \rightarrow O^*_{yt}$). In the data, we have different potential measures of police attention: arrests for different crimes. Suppose I_{yt} is the incidence of an illegal activity i. Then we can assume that arrests for a given activity i at time t in area y, are a function of police attention O^*_{yt} and the incidence of the legal activity I_{yt}:

$$A^i_{yt} = a(I_{yt}, O^*_{yt})$$

This simple reasoning reveals the importance of choosing a good measure for police attention. But what constitutes a good measure in this case? Our main objective is to explore how police attention varies with fights. Hence, a good measure of police attention in this context is the number of arrests for a type of crime that is unresponsive to fights: $\frac{\nabla I^*_{yt}}{\nabla F_{yt}} = 0$. If this is the case, then $\frac{\nabla A^{i^*}_{yt}}{\nabla F_{yt}} = \frac{\nabla O^*_{yt}}{\nabla F_{yt}}$. We choose arrests by local police as our measure of police attention. This enforcement agency, as explained in detail in Section 2.3, focuses on local law enforcement, traffic control, and urban regulation within specific city boundaries. Hence, it is unlikely to prosecute crimes that are responsive to gang fights.

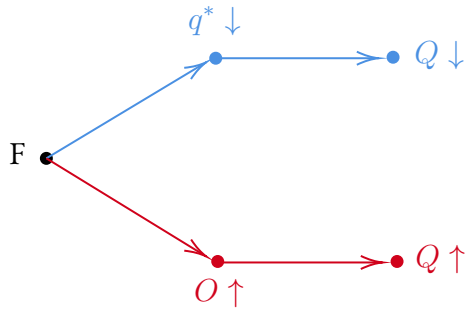
Estimation As a preliminary step, a subset of parameters are directly taken from the data $[p_{vt}, c_{vt}, k_{vt}, x_v]$. The estimation is carried out in four steps. First, the demand parameters $[\alpha_v, d_v, \mu_{vm}, \xi_y, \xi_t, \xi_v]$ are identified through the correlations between changes in seized drug quantities and changes in average prices, distance, and fights, controlling for seizure selection. Estimation procedure is an event-study with multiple fixed effects that exploits the linearity of the across areas unconditional demand 2, combined with a control function approach to deal with selection. Second, given fighting choices, we use data on fighting outcomes and decisions and their correlation with gang scale to estimate fighting parameters $[\psi, \phi_j, \Phi, \sigma_\epsilon]$ via simulated method of moments. Third, police attention parameters $[\lambda_m, \bar{o}_y]$ are identified with changes in the number of arrests following fight outbreaks. Estimation procedure is a difference in difference with fixed effects. Fourth, the remaining parameters governing fighting decisions $[\gamma, \delta]$ are estimated with MLE.

Model simplification We make a few simplifying assumptions to bring the model to the data. First, given the limited sample size, we reduce the number of demand parameters by assuming heterogenous preferences across drugs: $\{\alpha, d, \mu_m\}$. This is clearly a strong assumption. However, the limited sample size limit our power in investigating heterogenous consumer preferences. Second, we reduce the degree of heterogeneity across gangs. In particular, we reduce the

degree of heterogeneity to two type of gangs: small and large, as in the reduced form part of the paper. As a result, we only have two parameters of fighting ability (ϕ_s, ϕ_l), fight demand elasticity (μ_s, μ_l), and police reaction (λ_s, λ_l). We then normalize $\phi_s = 1$, so that ϕ_l should be interpreted in relative terms. Similarly, we normalize $\sigma_\gamma = 1$.

Preliminary step As a preliminary step for the estimation, a subset of parameters are directly taken from the data $[p_{vt}, c_{vt}, k_{vt}, x_v]$. In particular, average retail and wholesale prices are taken from the average official forms given to the antidrug authority by the enforcement authorities. The average price of cutting substances is set at 0.01 euros per gram. Average drug quality is set the average observed drug quality for cocaine and heroin and to 1 for marijuana - given that this drug is not cut.

First Step: Demand parameters The main parameter of interest in the demand equation is the (potentially heterogeneous) consumer preference from fight $\mu_m = (\mu_s, \mu_l)$. Naively, we would like to estimate it through changes in drug quantities with fights involving gangs of different scale. However, we do not observe the total quantity of drug sold in an area, but only the seized one. This introduces selection bias in our estimates. This is shown in the following directed graph:



Changes in drug seized at the fight outbreak is the composition of two effects: (i) the direct effect of the fight on the quantity sold, in blue, and (ii) the change in selection/seizures due to the fight, in red. In other words, without a method to isolate the selection effect, this preference parameter is not identified. To reach identification, we need to control for the change in seizure rate generated by an higher police attention in the area. To do so, we use a control function method. As in the Heckman, 1990 selection model, estimation follows a two step approach. First, we estimate the selection equation exploiting the correlation between the number of seizures N_{ytv} and a measure of police attention. Second, we estimate the log-linear demand *controlling* for the

change in selection:

$$\begin{aligned} &\text{1 step:} \quad log(N_{yvt}) = \eta O^*_{yt} + \gamma_1 p_{vt} + \gamma_2 F_{yt} + u_{yvt} \rightarrow log(\hat{N}_{ytv}) = \hat{\eta} O^*_{yt} \\ &\text{2 step:} \quad log(Q_{yvt}) = \alpha p_{vt} + \mu_m F_{ytm} + \nu log(\hat{N}_{ytv}) + f_y + f_v + f_t + \xi_{yvt} \end{aligned} \tag{8}$$

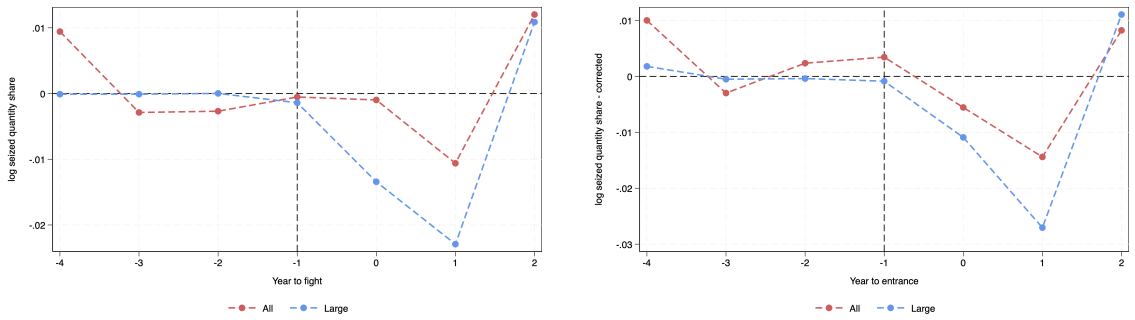
Where F_{ytm} is a dummy variable equal to one for the lead 0 and lead 1 of the first fight in the area, involving gangs of scale m. Hence, we use the predicted change in the number of seizures to control for changes in selection. Comparing how seized drug changes with fights, while controlling for the change in the number of seizures due to police attention, allows us to isolate the negative effect of fights on drug incidence. Identification relies on two assumptions:

Assumption - Exclusion restriction. $\mathbb{E}[O^*_{yt}(\xi_{yvt} + \epsilon_{ytv})] = 0$

Assumption - Conditional parallel trend. $\mathbb{E}[F_{ytm}(\xi_{yvt} + \epsilon_{ytv})|\hat{N}_{vyt}] = 0$

Appendix A.5 shows identification under these assumptions. A fundamental role is played by the measure of police attention, essentially serving as the instrumental variable for the number of seizures. This measure must be relevant for the number of seizures, while excluded from the demand equation. In other words, the only effect this should have on the quantity of drugs seized in the area must be through the number of drug seizures. Consequently, the choice of the measure of police attention is critical. For example, using the number of arrests for drug-related crimes is not probably appropriate, since it would likely impact the quantity of drugs seized through channels other than the seizure rate. We choose to use a measure of police attention which, while still being relevant for drug seizures, is unlikely to have any impact on the dynamics of the drug market: the (standardized) number of arrests by the local police. This police force, as explained in section 2, focuses on local law enforcement, traffic control, and urban regulations enforcement. Therefore, it is very unlikely to investigate drug-related crimes (indeed, the correlation between the two types of arrests is 0.0132, excluding Naples city). Moreover, as shown in section 4.1 there seems to be no correlation between the *average* amount of drug found – per seizure – and the number of arrests by local police. This suggest that consumers don't have a strong preference over the presence of municipal police, in line with drug consumption not being a major crime in Italy (more detail information on this in section 4.1). As a result, the exclusion restriction is much more likely to be satisfied.

Figure A38 presents the event study graph for the logarithm of the total amount of drugs seized at the onset of fights. As shown, there is no effect on the quantity of drugs seized at the outbreak of a fight. There appears to be some negative effect in the period following the outbreak,



Not controlling for selection Controlling for selection

Notes: This figure presents the share of drug seized, in a given year and for a given drug, in the area for each period relative to the fight outbreak, separately for a general fight, and a fight involving at least one large gang. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present.

Figure 5: Event study - seized quantity, mean

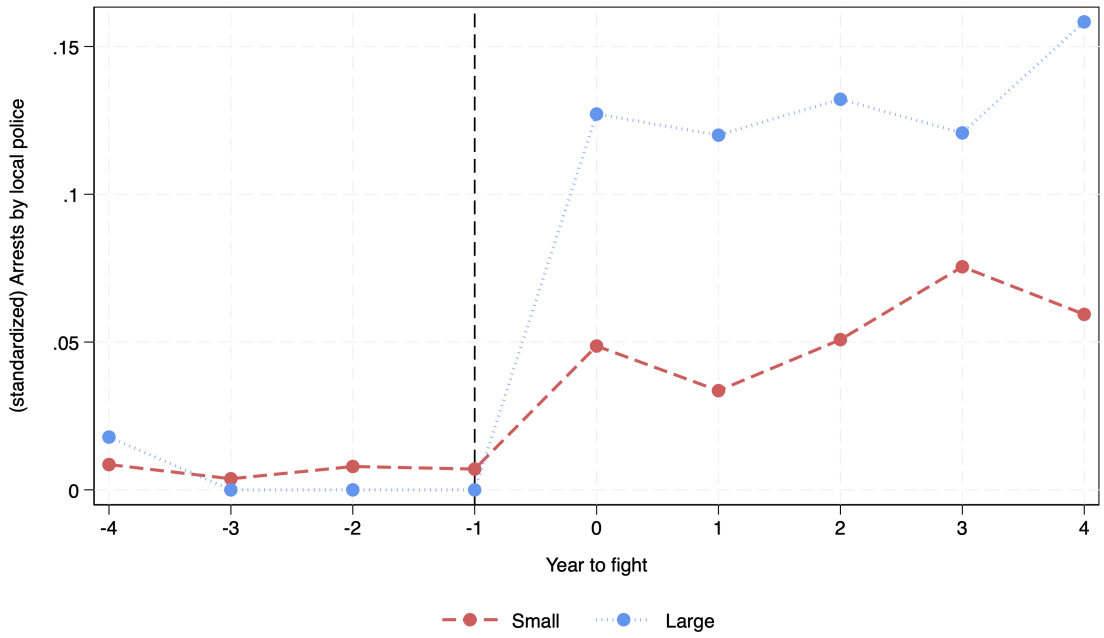
but it is very small and not statistically different from zero. However, these results represent the composition of the selection effect and the true effect on the drug market. Figure A39 replicates the event study controlling for selection (the predicted number of seizures). When doing so, a clear negative trend after the fight outbreak emerges, with the lead 1 coefficient being sizable and statistically different from zero. In other words, once we control for selection, we identify the negative effect of fights on drug dealing. In both figures, there seems to be no visible pre-trend before the fight, which provides reassurance about the validity of the conditional parallel trend assumption. Figure A40 replicates Figure A38 by showing the simple mean of the log seized quantity share (in each year, for each drug) controlling for city fixed effects. As one can see, the decline in the share of quantity seized is visible from the simple mean, and it is more pronounced when considering fights involving at least one large gang. In addition, in green we see the increasing trend in the number of seizures, also controlling for city fixed effects, although there is a visible pre-trend. Figure 5 replicates both Figures A38 abd A39 with raw data to facilitate comparison. Here, one can see the negative effect of fights, the stronger impact of fights involving larger gangs, and the role of controlling for selection.

Results of demand estimation are summarized in Table A6; in all models we include area, drug, and year fixed effects. In panel A, we show the second step of the estimation procedure. When not controlling for selection, first column, the negative correlation between fight outbreaks and the quantity of drugs seized is very small and not statistically different from zero (which is logical given that this represents the combination of a negative effect–the true effect on the market– and a positive one–the increase in seizures). However, once we control for selection in column 2, the negative effect becomes significantly larger and statistically different from zero at the 5% level.

In column 3 we introduce price in the model; the price coefficient is very small and not statistically different from zero, which is unsurprising given the limited variation in prices observed in the data. In column 4, instead of examining general fights, we explore the effect of fights involving at least one large gang. The decrease in the quantity seized, controlling for selection, is larger than with the whole set of fights, and statistically different from zero. To compare the effects of fights involving only small gangs with those involving large gangs, in column 5 we include both a dummy variable indicating a fight outbreak and its interaction with another dummy indicating whether the fight involved at least one large gang. This approach allows us to interpret the coefficient of the first variable as the negative effect of fights involving only small gangs, and the second coefficient as the additional negative impact when fights involve at least one large gang. Both coefficients are negative, with the second being substantially larger in magnitude, but only the first one is statistically significant. Thus, fights involving large gangs create more disruption in the market–consistently with the third fact presented in section 4.1–but this additional negative effect is very imprecisely estimated. Finally, in column 6 we instrument for retail prices using wholesale prices. The instrument is relevant, with a KP-statistic of 37.62. The price coefficient is now higher, but still not statistically significant. In panel B, we show the first step of the two-step procedure: the estimated selection equation. The standardized number of arrests by the local police is positively associated with the number of drug seizures, as expected, and this correlation is statistically different from zero at any conventional level. Unobserved preference parameters ξ_t, ξ_v, ξ_y are then recovered with the estimated fixed effects. Parameter d is then recovered from the estimated fixed effect $\hat{f}_y$ (panel C Table A6).

Second Step: Fighting parameters Fighting parameters $\{\phi_l, \Phi, \sigma_\epsilon\}$ are estimated via simulated method of moments, using data on fighting outcomes and decisions. In particular, we simulate the fighing process, described in section 4.5, of realized fights to match the realized outcomes. The estimation targets the following moments: increased probability of winning the fight if large, average probability of the fight ending in a win, and the variance in fighting outcomes. The increased probability of winning the fight for large gangs identifies the higher fighting ability of large gangs ϕ_l. Given the scale of the gangs involved in the fight, the average probability of the fight ending in a win identifies the scale of the fighting process Φ. Given scale and step, higher variance in fight outcomes indicates greater unpredictability in the fighting mechanism. Therefore, the variance in the probability of a gang winning a fight identifies σ_ϵ.

Third Step: Police reaction parameters Police reaction parameters $\{\bar{o}, \lambda_s, \lambda_l\}$ are esti-



Notes: This figure presents the share of arrests by local police, in a given year, in the area for each period relative to the fight outbreak, separately for a fight involving only small gangs, and a fight involving at least one large gang. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present.

Figure 6: Event study - arrests by local police, raw data

mated using the change in the number of arrests by local police following fights. Figure 6 shows these changes. In particular, we plot the standardized number of arrests by local police around the timing of fights, separately for fights involving only small gangs and those involving large gangs. We estimate the reaction parameters (λ_s, λ_l) using a simple difference-in-differences approach. For consistency with previous steps, we define the treatment dummy to cover only the first two years (lead 0 and lead 1) of the fight. Results are summarized in Table A7. Panel A shows estimates without fixed effects, while Panel B includes both city and year fixed effects. Results are consistent across panels: the number of arrests by local police increases with fights, but does so systematically more when fights involve at least one large gang. The average police attention parameter $\bar{o}$ is then recovered using the city fixed effect. This is translated into a unit (city+district) average police attention by dividing the obtained average by the number of districts in Naples.

Fourth Step: Other fighting parameters To conclude, we need to estimate the police attention cost δ and the average fixed cost from fighting $\bar{\gamma}$. We do so by maximum likelihood, maximizing the probability of observing the actual matrix of fights in the data. Intuitively, identification of

the fixed cost comes from the average fighting probability. Identification of the police cost comes from matching the different fighting propensities of large and small gangs. Given this estimation procedure, it is now clear why having a unique equilibrium in the probability of fights in the simple fighting game is important, as this allows us to construct the likelihood from the conditional choice probabilities. The estimation follows a three-step process. First, by simulating the model in the alternative scenarios, we compute the different profits $\{E\pi_j, E\pi_o, \pi_j^{NF}, \pi_j^p, \pi_o^{NF}, \pi_o^p\}$. Then, we use these profits to construct the likelihood:

$$\begin{aligned} L(\delta, \bar{\gamma}) = \textstyle\sum_{jo \in \mathcal{F}} 1[j \vee o \text{ large}]\{\Phi(E\pi_j - \delta\hat{\lambda}_l - \bar{\gamma} - \pi_j^p)\Phi(E\pi_o - \delta\hat{\lambda}_l - \bar{\gamma} - \pi_o^{NF}) + \\ + \Phi(E\pi_j - \delta\hat{\lambda}_l - \bar{\gamma} - \pi_j^{NF})\Phi(E\pi_o - \delta\hat{\lambda}_l - \bar{\gamma} - \pi_o^p)\} + \\ 1[j \wedge o \text{ small}]\{\Phi(E\pi_j - \delta\hat{\lambda}_s - \bar{\gamma} - \pi_j^p)\Phi(E\pi_o - \delta\hat{\lambda}_s - \bar{\gamma} - \pi_o^{NF}) + \\ + \Phi(E\pi_j - \delta\hat{\lambda}_s - \bar{\gamma} - \pi_j^{NF})\Phi(E\pi_o - \delta\hat{\lambda}_s - \bar{\gamma} - \pi_o^p)\} \end{aligned}$$

Where $\mathcal{F}$ is the set of all the possible dyads of gangs in the same locations. To conclude, we maximize the likelihood of observing the actual matrix of fights.

Estimation results Table 2 shows the results of the estimation. Here, we discuss the magnitude of the estimated parameters.

Panel A of Table 2 presents estimated parameters for the demand function. Price elasticity is negative but quite small, with a 1% increase in the cost of drugs being associated with a 0.83% decrease in quantity demanded. Moreover, the coefficient is not statistically different from zero at any conventional level. This is expected given the limited variation we have in prices in the sample. As expected, higher average distance of the area is associated with decreased quantity sold. Specifically, a 1% increase in km is associated with approximately 4.13% decrease in demand. In line with the evidence presented in fact 1 and 3, we find a negative and heterogeneous impact of fights. Specifically, a fight involving only small gangs decreases quantity by approximately 10%, while a fight involving at least one large gang by approximately 32%–equivalent to a 40% increase in price.

In Panel B we examine parameters governing the fighting process. In line with fact 2, the estimated fighting ability of large gangs is approximately 75% higher than that of smaller gangs, associated with a matched 8.4% increase in the probability of winning a fight. The estimated threshold fight is 3.23; importantly, this exceeds the largest difference between fighting abilities. This aligns with the matched 71% probability of a fight ending in a draw. The estimated fighting shock is quite high–1.72–consistent with high unpredictability in fighting outcomes.

In Panel C we discuss the remaining parameters, police reaction and other costs. As expected

Table 2: Estimated parameters

Variable	Notation	Estimate	S.e.	Elasticity
Panel A: Demand				
Price	α	-0.00016	0.0023	-0.83% (1% ↑ euro)
Trasportation cost	d	-0.0010	0.0002	-4.13% (1% ↑ km)
Fight disutility (small)	μ_s	-0.0094	0.0057	-9.57%
Fight disutility (large)	μ_l	-0.0263	0.0211	-31.92%
Panel B: Fighting				
Fighting ability large	ϕ_l	1.75		matched ≈ 8.4% higher win
Threshold fight	Φ	3.23		matched ≈ 17.7% win probability
Dispersion shock	σ_ϵ	1.72		matched ≈ 14% variance in win
Panel C: Other				
Increase police (small)	λ_s	0.00084	0.00499	↑ 15% increase
Increase police (large)	λ_l	0.02436	0.008989	↑ 437% increase
Police cost	δ	9.50817	11.71543	↓ 19.02% average profit
Fight fixed cost	γ	1.41284	0.12818	

from the evidence presented in Section 4.1 and the data shown in Figure 6, we find an heterogeneous impact of fights on police attention. A fight involving only small gangs, increase police attention by 15% with respect to the sample mean. If the fight involves at least one large gang, instead, this effect is much larger, amounting to approximately 440% of the sample mean. Fights involving larger gangs generate dramatically more violence, which then translates into an significantly stronger police response. To conclude, unsurprisingly, police attention is costly for criminal firms. In particular, 1% increase in police attention is associated with a 19% decrease in average peace profits.

Model fit Figures A41 and A42 test the demand model fit by comparing, across areas, drugs, and years, the observed drug quantity share seized with that predicted by the model, both with and without Naples respectively. The demand model fit is good, showing a strong positive correlation in both graphs. Predicted quantity is consistently higher than the seized quantity, which is reasonable to expect given the seizure selection process. The correlation between standardized measures of quantity is approximately 40%. Table A8 reports the correlation between the

observed share and the simulated share, controlling for drug, year, and city fixed effects. The correlation is positive and statistically different from zero in all models.

Figure A43 shows the correlation between the number of fight and predicted probability of fight one in 2022.[11] If we define a predicted fight to happen when the predicted probability is higher than the third quintile, we would predict 5 out of 6 fights happening in 2022 – correctly guessing both the gang dyad and the area involved. Is this prediction good only because of the MLE estimation? Or, instead, is our model capturing some important determinant in the occurrence of fights? To answer this question, in Figures A44 and A45 we plot the observed fight probability over two ratios: expected profits over peace profits and expected profits over exit (non-fight) ones. In line with the model, we find an higher probability of fights occurring when expected profits from doing so, relative to the outside option – peace or exit – is higher (although not symmetrically for the peace ratio). In other words, we find an higher probability of fights in the data when the model is suggesting so. To conclude, in Table A9 we explore the correlation between realized fights in the whole sample (column 1), in 2022 (column 2), and predicted fight probabilities in the same period in column 3. All correlations are of the expected sign, and in similar magnitude between the model and the data. In particular, we find a postive correlation between the location fixed effect in demand estimation, measuring the unobserved location preference, and fights probabilities. In other words, we observe more fights in "valuable" areas, but in the data and in the model. The same reasoning can be applied to the maximum scale of the gang in the area, with areas having larger gangs being associated with a lower fight probability both in the observed and predicted probabilities. An higher number of gangs is associated with a higher observed and simulated fight probabilities. To conclude, an higher heterogeneity in scale of gangs present in the area is associated with a lower fighting probability in the data, in line with evidence presented in Section 3, and in the model too.

6 Counterfactuals

In this section, we perform counterfactual scenarios to (1) test the mechanisms behind the negative correlation between gang size and violence, and (2) explore the relationship between market concentration and violence.

[11] Due to time limitations, we simulate the model for 2022 only, the last year of our sample.

6.1 Mechanisms

Table 3 shows the fighting probability, computed separately for small and large gangs in 2022 in the data, as simulated by the model, and across the different counterfactual scenarios. In the data, this is computed as the number of realized fights over all the possible combinations of gangs in the same location. In the model, this is simply the average of predicted fighting probabilities. In line with the evidence presented in Section 3, the observed fighting probability is significantly lower for larger gangs with respect to smaller ones (-58.61%). Not surprisingly, the fighting probabilities predicted by the model are very similar to the observed ones, with a -56.85% average fighting probability for large gangs.

Table 3: Counterfactual - mechanisms

		Small	**Large**	**Perc. change**
Data		0.0151976	0.0062893	-58.61%
Simulation model	$\phi_s = 1, \phi_l = 1.75$ $\mu_s = -0.0094, \mu_l = -0.0263$ $\lambda_s = 0.0008, \lambda_l = 0.0244$	0.0147907	0.0063825	-56.85%
No deterrence	$\phi_s = 1.75, \phi_l = 1.75$ $\mu_s = -0.0094, \mu_l = -0.0263$ $\lambda_s = 0.0008, \lambda_l = 0.0244$	0.0145706	0.00632800	-56.57%
No demand	$\phi_s = 1, \phi_l = 1.75$ $\upsilon_s = -0.0094, \upsilon_l = -0.0094$ $\lambda_s = 0.0008, \lambda_l = 0.0244$	0.0147907	0.00644200	-56.44%
No self-regulation	$\phi_s = 1, \phi_l = 1.75$ $\upsilon_s = -0.0094, \upsilon_l = -0.0263$ $\lambda_s = 0.0008, \lambda_l = 0.0008$	0.0147907	0.0150198	1.54%

Notes: Table displays the average fighting probability, separately for small and large gangs, in the data, and in different counterfactual scenarios. Fighting probability is computed as the number of realized fights over all the possible combinations of gangs in the same location in the data, and in the models it is simply the average of predicted fighting probabilities. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present.

We can then use the model to test the mechanisms by running counterfactual simulations. In the first simulation, we test the deterrence mechanism by counterfactually eliminating any difference in fighting outcome probabilities between large and small gangs (i.e. by setting $\phi_l = \phi_s = 1.75$).This change has two distinct effects. On the one hand, it decreases the probability of large gangs winning fights against small ones, which should decrease the expected benefits of fighting for these gangs. On the other hand, it also decreases the probability of smaller gangs losing against large ones, which increases the expected profit of fighting for smaller gangs. If the mechanism be-

hind our results were deterrence, where smaller gangs choose to avoid confrontation with larger ones, then this counterfactual scenario should eliminate this effect, and we would observe higher or equal fighting propensity among larger gangs. However, this is not the case. Instead, changing this parameter has little effect on the fighting propensities predicted by the model. This makes sense, given the very low fighting premium (+8% probability of winning fights, compared to an average of 71% of fights ending in draws) enjoyed by gangs in this setting.

To test the demand mechanism, we counterfactually equalize the demand reaction to fights involving gangs of different scales (i.e. formally set $\mu_l = \mu_s = -0.0094$). As expected, the fighting propensity slightly increases for large gangs, given that fights are now less costly on average, resulting in a small increase in the difference in fighting probabilities. Therefore, the demand mechanism appears to be active, although its role in explaining the observed difference is quite limited.

Finally, we test the self-regulation mechanism by equalizing the increase in police attention that fights with different gangs generate: $\lambda_l = \lambda_s = 0.0008$. In this counterfactual scenario, the fighting probability of large gangs increases significantly, even reversing the difference from approximately -56% to +1%. Therefore, if gangs of different scales were to attract the same attention from the regulator, larger gangs would fight more–or at a similar propensity.

6.2 Market concentration and violence

Thanks to the model, we can now change the structure of the market to explore the relationship between market concentration and violence.

In particular, we randomly "merged" gangs to increase market concentration in 10 scenarios ranging from perfect competition with no large gangs to a monopoly. It is important to note that market shares *within* areas are fixed and equal to 1 divided by the number of gangs present. Hence, variation in HHI stems from market shares of the areas and the presence of large gangs, which aggregate all the simple market shares in the areas in which they are present. Results are presented in Figure 7. The vertical line is the true HHI, equal to approximately 1%.

The overall relationship is non-linear. Moving from perfect competition to monopoly: the atomistic market is moderately violent, with a relatively high probability of fights occurring. As market concentration begins to increase and some large gangs appear, the probability of fights increases even further. Introducing very few large players into a continuum of very small gangs disrupts the equilibrium, substantially decreasing the unpredictability of fights and, therefore, stimulating violence. This pattern continues until we reach a first tipping point. Beyond this point, the further we increase market concentration, the lower the predicted probability of fights

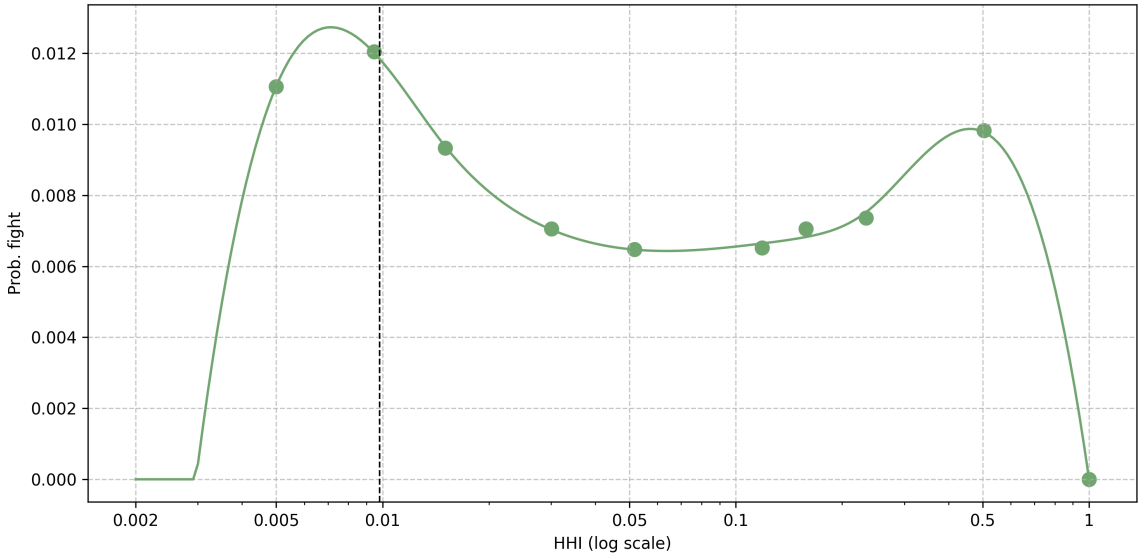


Figure 7: Counterfactual - market concentration

becomes. Here, the additional increase in the predictability of fights is not sufficient to counter the combined effects of fewer gangs in the market and the increasing costs of fighting. At the other extreme of the market concentration distribution, this relationship reverses again, due to expected benefits from fighting increasing non-linearly. Finally, in a monopoly there is trivially no fighting.

This non-linear relationship between market concentration and violence has important implications for gang crackdown strategies, revealing why traditional enforcement approaches sometimes backfire. In nearly atomistic markets composed of very small groups/individual criminals, targeting slightly larger gangs may be effective in both reducing criminal activity and violence. However, this is not the case in oligopolistic markets in the middle of the concentration distribution. In this case, when large criminal organizations are fragmented into smaller groups, markets move from relatively peaceful concentrated states back toward highly violent equilibria. This explains why many aggressive enforcement campaigns have resulted in increased rather than decreased violence, as in numerous real-world examples.

One of these examples is the famous Mexico's "kingpin strategy" under President Calderón (2006-2012) provides the most striking illustration of this idea. The systematic targeting of cartel leaders led to a decrease in market concentration and a dramatic surge in violence. The number of organized crime groups skyrocketed from 67 around 2009 to 205 in 2020. At the same time, homicide rate per 100k people has increased from 8.19 in 2007 to 23.84 in 2011, and 29.19 in

2020.[12]

The model's implications suggest that effective gang policy requires understanding market structure dynamics rather than applying uniform crackdown strategies. In highly fragmented markets, removing larger players may reduce violence, while in concentrated markets, a trade-off emerges between reducing market concentration and violence. Here, the focus should shift to preventing fragmentation when targeting large organizations. Alternative strategies might include policies that artificially increase the costs of fighting rather than simply removing players, territorial agreements that reduce competition, or comprehensive approaches that combine enforcement with social investment to reduce the attractiveness of criminal careers. The key insight is that the same enforcement action can have opposite effects depending on the initial market structure, making context-specific strategies essential for success.

7 Conclusions

This paper provides novel empirical evidence on the relationship between market concentration and violence in illegal markets. Leveraging new intelligence data from Naples' drug market, we show that larger gangs are less violent. Our counterfactual simulations show that this is true because larger gangs self-regulate themselves to avoid the strong police response. To conclude, we find a non linear relationship between market concentration and violence. These findings have important implications for enforcement strategies in illegal markets, suggesting that interventions may have different effects depending on the underlying market structure.

This paper provides an initial framework for understanding the relationship between market structure and violence in illegal markets, yet important avenues for future research remain. Our static model abstracts from coalition formation dynamics, where gangs may form alliances to coordinate territorial control or respond to law enforcement pressure. Incorporating endogenous coalition formation would reveal how alliance structures affect market concentration and violence patterns. Additionally, extending the analysis to incorporate inter-temporal strategic decisions represents another promising direction. Criminal organizations anticipate future competitive dynamics and enforcement responses when making current violence decisions. A dynamic model could illuminate phenomena such as preemptive territorial expansion or strategic restraint to avoid regulatory attention.

[12]Source on the number of gangs: https://mwi.westpoint.edu/why-mexicos-kingpin-strategy-failed-targeting-leaders-led-to-more-criminal-groups-and-more-violence/. Source on the homicide per capita: https://www.macrotrends.net/global-metrics/countries/mex/mexico/murder-homicide-rate

References

Aguirregabiria, V., & Vicentini, G. (2016). Dynamic spatial competition between multi-store retailers. *The Journal of Industrial Economics*, *64*(4), 710–754.

Alesina, A., Piccolo, S., & Pinotti, P. (2019). Organized crime, violence, and politics. *The Review of Economic Studies*, *86*(2), 457–499.

Barbagallo, F. (2014). *Storia della camorra*. Gius. Laterza & Figli Spa.

Becucci, S. (2004). Old and new actors in the italian drug trade: Ethnic succession or functional specialization? *European Journal on Criminal Policy and Research*, *10*, 257–283.

Berry, S. T. (1992). Estimation of a model of entry in the airline industry. *Econometrica*, 889–917.

Blattman, C., Duncan, G., Lessing, B., & Tobón, S. (2024). Gang rule: Understanding and countering criminal governance. *Review of Economic Studies*.

Brancaccio, L., & Martone, V. (2019). The camorras in naples and campania: Business, groups and families. In *Italian mafias today* (pp. 30–46). Edward Elgar Publishing.

Brown, Z. Y., Montero, E., Schmidt-Padilla, C., & Sviatschi, M. M. (2024). Market structure and extortion: Evidence from 50,000 extortion payments. *Review of Economic Studies*.

Bruhn, J., et al. (2021). Competition in the black market: Estimating the causal effect of gangs in chicago.

Buchanan, J. M. (1973). A defense of organized crime. *The economics of crime and punishment*, *119*, 119.

Campaniello, N., Gray, R., & Mastrobuoni, G. (2016). Returns to education in criminal organizations: Did going to college help michael corleone? *Economics of Education Review*, *54*, 242–258.

Catino, M. (2014). How do mafias organize?: Conflict and violence in three mafia organizations. *European Journal of Sociology/Archives Europeennes de Sociologie*, *55*(2), 177–220.

Catino, M. (2019). *Mafia organizations*. Cambridge University Press.

Ciliberto, F., & Tamer, E. (2009). Market structure and multiple equilibria in airline markets. *Econometrica*, *77*(6), 1791–1828.

Clarke, D., & Tapia Schythe, K. (2023). Eventdd: Stata module to panel event study models and generate event study plots.

Cook, P. J., Ludwig, J., Venkatesh, S., & Braga, A. A. (2007). Underground gun markets. *The Economic Journal*, *117*(524), F588–F618.

DCSA. (2024). *Relazione annuale direzione centrale servizi antridroga 2024* (Tech. Rep.).

Dell, M. (2015). Trafficking networks and the mexican drug war. *American Economic Review*,

105(6), 1738–1779.

DIA. (2015). *Relazione del ministreo dell'interno al parlamento: attività svolta e risultati conseguiti dalla direzione investigativa antimafia* (Tech. Rep.).

DIA. (2020). *Relazione del ministreo dell'interno al parlamento: attività svolta e risultati conseguiti dalla direzione investigativa antimafia* (Tech. Rep.).

DIA. (2022). *Relazione del ministreo dell'interno al parlamento: attività svolta e risultati conseguiti dalla direzione investigativa antimafia* (Tech. Rep.).

Donohue, J. J., & Levitt, S. D. (1998). Guns, violence, and the efficiency of illegal markets. *The American Economic Review*, *88*(2), 463–467.

Dugato, M., Calderoni, F., & Berlusconi, G. (2020). Forecasting organized crime homicides: Risk terrain modeling of camorra violence in naples, italy. *Journal of interpersonal violence*, *35*(19-20), 4013–4039.

EMCDDA. (2013). *European monitoring centre for drugs and drug addiction: Drug report* (Tech. Rep.). European Monitoring Centre for Drugs and Drug Addiction.

Erfle, S., & McMillan, H. (1990). Media, political pressure, and the firm: The case of petroleum pricing in the late 1970s. *The Quarterly Journal of Economics*, *105*(1), 115–134.

Eurispes. (2005). *Rapporto italia 2005* (Tech. Rep.).

Fox, A. M., Katz, C. M., Choate, D. E., & Hedberg, E. C. (2015). Evaluation of the phoenix truce project: a replication of chicago ceasefire. *Justice Quarterly*, *32*(1), 85–115.

Galenianos, M., & Gavazza, A. (2017). A structural model of the retail market for illicit drugs. *American Economic Review*, *107*(3), 858–896.

Galenianos, M., Pacula, R. L., & Persico, N. (2012). A search-theoretic model of the retail market for illicit drugs. *The Review of Economic Studies*, *79*(3), 1239–1269.

Gambetta, D., & Reuter, P. (2017). Conspiracy among the many: the mafia in legitimate industries. In *Transnational organized crime* (pp. 247–266). Routledge.

Goldberg, P. K. (1995). Product differentiation and oligopoly in international markets: The case of the us automobile industry. *Econometrica*, 891–951.

Goldberg, P. K., & Verboven, F. (2001). The evolution of price dispersion in the european car market. *The Review of Economic Studies*, *68*(4), 811–848.

Gribaudi, M. G., et al. (2009). Clan camorristi a napoli: radicamento locale e traffici internazionali. In *Traffici criminali. camorra, mafie e reti internazionali dell'illegalità* (pp. 187–240). Bollati Boringhieri.

Heckman, J. (1990). Varieties of selection bias. *The American Economic Review*, *80*(2), 313–318.

Holmstrom, B. R., & Tirole, J. (1989). The theory of the firm. *Handbook of industrial organi-*

zation, *1*, 61–133.

Kar, D., & Spanjers, J. (2017). Transnational crime and the developing world. *Global Financial Integrity*, 53–59.

Le Moglie, M., & Sorrenti, G. (2020). Revealing maiia inc. financial crisis, oc, and the birth oi new enterprises. *The Review of Economics and Statistics, pp. 145*.

Levitt, S. D., & Venkatesh, S. A. (2000). An economic analysis of a drug-selling gang's finances. *The Quarterly Journal of Economics*, *115*(3), 755–789.

Marrazzo, G. (2005). *Il camorrista*. Tullio Pironti Editore.

Mastrobuoni, G., & Patacchini, E. (2012). Organized crime networks: An application of network analysis techniques to the american mafia. *Review of Network Economics*, *11*(3).

Mazzeo, M. J. (2002). Product choice and oligopoly market structure. *RAND Journal of Economics*, 221–242.

Melnikov, N., Schmidt-Padilla, C., & Sviatschi, M. M. (2020). *Gangs, labor mobility and development* (Tech. Rep.). National Bureau of Economic Research.

Mirenda, L., Mocetti, S., & Rizzica, L. (2022). The economic effects of mafia: firm level evidence. *American Economic Review*, *112*(8), 2748–2773.

Monnier, M. (1862). *La camorra notizie storiche raccolte e documentate*. G. Barbera.

Monteiro, J., & Rocha, R. (2017). Drug battles and school achievement: evidence from rio de janeiro's favelas. *Review of Economics and Statistics*, *99*(2), 213–228.

Pinotti, P. (2015). The economic costs of organised crime: Evidence from southern italy. *The Economic Journal*, *125*(586), F203–F232.

Polo, M. (1995). Internal cohesion and competition among criminal organizations. *The economics of organised crime*, 87–115.

Reiss, P., & Bresnahan, T. (1990). Entry in monopoly markets. *Review of Economic Studies*, *57*(4), 531–53.

Reuter, P. (2014). Drug markets and organized crime. *The Oxford handbook of organized crime*, 359–381.

Sales, I. (1994). *La camorra, le camorre*. Editori Riuniti.

Sales, I. (2022). *Storia delle camorre: passato e presente*. Rubbettino.

Salop, S. C. (1979). Strategic entry deterrence. *The American Economic Review*, *69*(2), 335–338.

Schelling, T. C. (1967). Economics and criminal enterprise. *The Public Interest*, *7*, 61.

Transcrime, C. (2013). Progetto pon sicurezza 2007–2013. gli investimenti delle mafie. *Rapporto Linea*, *1*.

Appendix

A Proofs and Derivations

A.1 Derivation demand

Consumer problem Consumer solves:

$$\begin{gathered}\max_{d_{(y,j)}} \sum_{(y,j)} d_{(y,j)} \mathbb{E}u_{ijyvt} \quad \forall v, t \\ \text{s.t.} \sum_{(y,j)} d_{(y,j)} = 1\end{gathered}$$

Since in this model an individual is defined by product specific shocks $(\epsilon_{ijvt}, \epsilon_{iyvt})$, this implictly defines the set of individual attributes that lead to the purchase of good (j, y). Formally:

$$A_{jy} = \{(\epsilon_{ijvt}, \epsilon_{iyvt}) | \mathbb{E}u_{ijyvt} \geq \mathbb{E}u_{i\tilde{j}\tilde{y}vt} \forall \tilde{j} \in \mathcal{J} \text{ and } \forall \tilde{y} \in \mathcal{Y}\}$$

Assuming ties occur with zero probability, and the iid nature of the two EVT1 shocks, the market share of the (j, y) bundle is just an integral over the mass of consumers in region A_{jyv}:

$$s_{jyvt} = \int_{A_{jy}} dP(\epsilon_{ijvt}, \epsilon_{iyvt}) =^{iid} \int_{A_{jy}} dP(\epsilon_{ijvt}) P(\epsilon_{iyvt})$$

We will now work to find an explicit expression definying the set A_{jy}. In particular, we will exploit the nested structure of the model. Notice that we can decompose:

$$P(ivt \in A_{jy}) = P_{ivt \to jy} = P_{ivt \to j|y} \times P_{ivt \to y}$$

In the remaining of this section we will derive an expression for these two probabilities.

Within nests Let's start with $P_{ivt \to j|y}$. A consumer in area y chooses the organization which gives him the highest utility. Formally:

$$\begin{gathered}P_{ivt \to j|y} = P(u_{ijyvt} \geq u_{i\tilde{j}yvt} \, \forall \tilde{j} \in \mathcal{J}_y) = \\ = P(\delta_{jyvt} + d_v g_{iy} + \epsilon_{ijvt} + \epsilon_{ijvt} \geq \delta_{\tilde{j}yvt} + d_v g_{iy} + \epsilon_{i\tilde{j}vt} + \epsilon_{iyvt} \, \forall \tilde{j} \in \mathcal{J}_y) \\ = P(\epsilon_{i\tilde{j}vt} \leq \epsilon_{ijvt} + \delta_{jyvt} - \delta_{\tilde{j}yvt} \, \forall \tilde{j} \in \mathcal{J}_y)\end{gathered}$$

Since the ϵ_s are indipendent, this set comulative distribution can be rewritten as the product of the individual comulative distributions:

$$P_{ivt \to j|y} | \epsilon_{ijvt} = \prod_{\tilde{j} \in y - j} \exp[-\exp[\epsilon_{ijvt} + \delta_{jyvt} - \delta_{\tilde{j}yvt}]]$$

The problem with the expression is that we don't know ϵ_{ijvt}. So we integrate it away:

$$P_{ivt\to j|y} = \int_{-\infty}^{+\infty} [\prod_{\tilde{j}\in y-j} e^{-e^{-[\epsilon_{ijvt}+\delta_{jyvt}-\delta_{\tilde{j}yvt}]}}] e^{-\epsilon_{ijvt}} e^{e^{-\epsilon_{ijvt}}} d\epsilon_{ijvt}$$

Since $\delta_{jyvt} - \delta_{jyvt} = 0$ we can rewrite the integral as:

$$P_{ivt\to j|y} = \int_{-\infty}^{+\infty} [\prod_{\tilde{j}\in y} e^{-e^{-[\epsilon_{ijvt}+\delta_{jyvt}-\delta_{\tilde{j}yvt}]}}] e^{-\epsilon_{ijvt}} d\epsilon_{ijvt} =$$
$$= \int_{-\infty}^{+\infty} [\prod_{\tilde{j}\in y} e^{-e^{-\epsilon_{ijvt}} e^{-[\delta_{ijyvt}-\delta_{i\tilde{j}yvt}]}}] e^{-\epsilon_{ijvt}} d\epsilon_{ijvt}$$

Define $t = e^{\epsilon_{ijvt}}$ and let's change variable with $d\epsilon_{ijvt} = \frac{1}{t} dt$:

$$P_{ivt\to j|y} = \int_0^{+\infty} e^{-t[\sum_{\tilde{j}\in y} e^{-[\delta_{ijyvt}-\delta_{i\tilde{j}yvt}]}]} dt =$$
$$= [-\frac{e^{-t[\sum_{\tilde{j}\in y} e^{-[\delta_{ijyvt}-\delta_{i\tilde{j}yvt}]}]}}{\sum_{\tilde{j}\in y} e^{-[\delta_{ijyvt}-\delta_{i\tilde{j}yvt}]}}]_0^{\infty} =$$
$$= 0 + \frac{1}{\sum_{\tilde{j}\in y} e^{-[\delta_{ijyvt}-\delta_{i\tilde{j}yvt}]}} = \frac{\exp(\delta_{jyvt})}{\sum_{\tilde{j}\in y} \exp(\delta_{\tilde{j}yvt})}$$

Across nests Now we need to compute the second probability: $P_{ivt\to y}$. The maximum utility from nest/area y is:

$$\begin{cases} \max_{j\in y} u_{ijyvt} & y \neq 0 \\ 1 & y = 0 \end{cases}$$

where the second case comes from the normalization of expected utility of outside option. Substituting our equation for the indirect utility:

$$\max_{j\in y} \delta_{jyvt} + \epsilon_{iyvt} + \epsilon_{ijvt} + d_v g_{iy} =$$
$$= (\max_{j\in y} \alpha_v p_{vt} + \mu_v V_{yt} + \xi_{yvt} + \epsilon_{ijvt}) + \epsilon_{iyvt} + d_v g_{iy} =$$
$$= (\max_{j\in y} \epsilon_{ijvt}) + \mu_v V_{yt} + \alpha_v p_{vt} + \xi_{yvt} + \epsilon_{iyvt} + d_v g_{iy} =$$
$$= (\max_{j\in y} \epsilon_{ijvt}) + \mu_v V_{yt} + \alpha_v p_{vt} + \xi_{yvt} + \epsilon_{iyvt} + d_v g_{iy}$$

Due to the extreme value properties of the ETV1 component we have (approximation of the expectation of the maximum of an ETV1 distribution):

$$\mathbb{E}(\max_{j\in y} \epsilon_{ijvt}) \approx \gamma$$

Substituting into the previous problem:

$$(\max_{j\in y} u_{ijyvt}) \approx \alpha_v p_{vt} + \xi_{yvt} + \epsilon_{iyvt} + d_v g_{iy} + \gamma$$

Hence the maximum expected indirect utility is:

$$V_{iyvt} = \bar{\delta}_{yvt} + \epsilon_{iyvt} + d_v g_{iy} + \gamma$$

Similarly to the reasoning done before, the consumer chooses the nest which gives him the highest expected utility:

$$P_{ivt\to y} = P(V_{iyvt} \geq V_{i\tilde{y}vt}\ \forall \tilde{y} = 0, 1, ..., Y)$$

Hence:

$$\begin{aligned} P_{ivt\to y} = P(\bar{\delta}_{yvt} + \epsilon_{iyvt} + d_v g_{iy} + \gamma \geq \bar{\delta}_{\tilde{y}vt} + \epsilon_{i\tilde{y}vt} + d_v g_{i\tilde{y}} + \gamma) \forall \tilde{y} \in \mathcal{Y} = \\ = P(\epsilon_{i\tilde{y}vt} \leq \epsilon_{iyvt} + \bar{\delta}_{yvt} - \bar{\delta}_{\tilde{y}vt} + d_v g_{iy} - d_v g_{i\tilde{y}}) \end{aligned}$$

To simplify notation, let's denote: $M_{yvt} = \bar{\delta}_{yvt} + d_v g_{iy}$. Therefore:

$$P_{ivt\to y}|\epsilon_{iyvt} = \prod_{\tilde{y}\in\mathcal{Y}/y} \exp(-\exp(M_{yvt} - M_{\tilde{y}vt}))$$

As before, the problem with the expression is that we don't know ϵ_{iyvt}. So we integrate it away:

$$P_{ivt\to y} = \int_{-\infty}^{+\infty} [\prod_{\tilde{y}\in\mathcal{Y}/y} e^{-e^{-[\epsilon_{iyvt} + M_{yvt} - M_{\tilde{y}vt}]}}] e^{-\epsilon_{iyvt}} e^{e^{-\epsilon_{iyvt}}} d\epsilon_{iyvt}$$

Since $M_{yvt} - M_{yvt} = 0$ we can rewrite the integral as:

$$\begin{aligned} P_{ivt\to y} = \int_{-\infty}^{+\infty} [\prod_{\tilde{y}\in\mathcal{Y}} e^{-e^{-[\epsilon_{iyvt} + M_{yvt} - M_{\tilde{y}vt}]}}] e^{-\epsilon_{iyvt}} d\epsilon_{iyvt} = \\ = \int_{-\infty}^{+\infty} [\prod_{\tilde{y}\in\mathcal{Y}} e^{-e^{-\epsilon_{iyvt}} e^{-[M_{yvt} - M_{\tilde{y}vt}]}}] e^{-\epsilon_{iyvt}} d\epsilon_{iyvt} \end{aligned}$$

Define $t = e^{\epsilon_{iyvt}}$ and let's change variable with $d\epsilon_{iyvt} = \frac{1}{t} dt$:

$$\begin{aligned} P_{ivt\to y} = \int_0^{+\infty} e^{-t[\sum_{\tilde{y}\in\mathcal{Y}} e^{-[M_{yvt} - M_{\tilde{y}vt}]}]} dt = = [-\frac{e^{-t[\sum_{\tilde{y}\in\mathcal{Y}} e^{-[M_{yvt} - M_{\tilde{y}vt}]}]}}{\sum_{\tilde{y}\in\mathcal{Y}} e^{-[M_{yvt} - M_{\tilde{y}vt}]}}]_0^{\infty} = \\ = 0 + \frac{1}{\sum_{\tilde{y}\in\mathcal{Y}} e^{-[M_{yvt} - M_{\tilde{y}vt}]}} = \frac{\exp(M_{yvt})}{\sum_{\tilde{y}\in\mathcal{Y}} \exp(M_{\tilde{y}vt})} = \\ = \frac{\exp(\bar{\delta}_{yvt} + d_v g_{iy})}{1 + \sum_{\tilde{y}\in\mathcal{Y}} \exp(\bar{\delta}_{\tilde{y}vt} + d_v g_{i\tilde{y}})} \end{aligned}$$

Before turning to the unconditional demand, we will now see how to transform this across nest share into an unconditional demand for drugs in area y. The unconditional demand for drugs in nest y can be written as weighted sum of the conditional demands:

$$s_{yvt} = \sum_{y_i} \frac{M_{y_i}}{\sum_y M_y} s_{yvt|y_i} = \sum_{y_i} \frac{M_{y_i}}{\sum_y M_y} \frac{\exp(\bar{\delta}_{yvt} + d_v g_{iy})}{1 + \sum_{\tilde{y}\in\mathcal{Y}} \exp(\bar{\delta}_{\tilde{y}vt} + d_v g_{i\tilde{y}})}$$

Denote by $S_{vt} = 1 + \sum_{\tilde{y}\in\mathcal{Y}} \exp(\bar{\delta}_{\tilde{y}vt} + d_v g_{i\tilde{y}})$, and $Z_{yvt} = \bar{\delta}_{yvt}$. Taking logs:

$$\begin{aligned} log(s_{yvt}) = log(\sum_{y_i} \frac{M_{y_i}}{\sum_y M_y} s_{yvt|y_i}) = log(\sum_{y_i} \frac{M_{y_i}}{\sum_y M_y} \frac{\exp(Z_{yvt} + d_v g_{iy})}{S_{vt}}) = \\ = log(\frac{1}{S_{vt}} \sum_{y_i} \frac{M_{y_i}}{\sum_y M_y} exp(Z_{yvt}) exp(d_v g_{iy})) = \\ = log(\frac{1}{S_{vt}} exp(Z_{yvt}) \sum_{y_i} \frac{M_{y_i}}{\sum_y M_y} exp(d_v g_{iy})) = \\ = -log(S_{vt}) + Z_{yvt} + log(\sum_{y_i} \frac{M_{y_i}}{\sum_y M_y} exp(d_v g_{iy})) = \\ = -log(S_{vt}) + \bar{\delta}_{yvt} + log(\sum_{y_i} \frac{M_{y_i}}{\sum_y M_y} exp(d_v g_{iy})) \end{aligned}$$

Which, by adding the fixed effects, becomes equation 2.

Unconditional demand Finally, we can put toghether the two probabilities to compute the probability of consumer i choosing the bundle (j, y) for drug v at t:

$$P(ivt \in A_{jy}) = P_{ivt \to jy} = \frac{\exp(\delta_{jyvt})}{\sum_{\tilde{j} \in y} \exp(\delta_{\tilde{j}yvt})} \times \frac{\exp(\bar{\delta}_{yvt} + d_v g_{iy})}{1 + \sum_{\tilde{y} \in \mathcal{Y}} \exp(\bar{\delta}_{\tilde{y}vt} + d_v g_{i\tilde{y}})}$$

Demand is represented by this set of individual probabilities:

$$P_{ivt \to jy} = \frac{\exp(\delta_{jyvt}) \exp(\bar{\delta}_{yvt} + d_v g_{iy})}{\sum_{\tilde{j} \in y} \exp(\delta_{\tilde{j}yvt})[1 + \sum_{\tilde{y} \in \mathcal{Y}} \exp(\bar{\delta}_{\tilde{y}vt} + d_v g_{i\tilde{y}})]} \tag{9}$$

To conclude, we need to compute the market shares. Returning to our first derivations we have:

$$s_{jyvt} = \int_{A_{jy}} dP(\epsilon_{ijvt}) P(\epsilon_{iyvt}) \approx \sum_{y_i} \frac{M_{y_i}}{\sum_y M_y} \frac{\exp(\delta_{jyvt}) \exp(\bar{\delta}_{yvt} + d_v g_{iy})}{\sum_{\tilde{j} \in y} \exp(\delta_{\tilde{j}yvt})[1 + \sum_{\tilde{y} \in \mathcal{Y}} \exp(\bar{\delta}_{\tilde{y}vt} + d_v g_{i\tilde{y}})]}$$

These individual buying probabilities can be used to compute the aggregate demanded quantities.

Denote by D_v the average annual amount of drug bought by an average consumer of drug v. Then:

$$q_{jyvt} \approx D_v \sum_{y_i} M_{y_i} \frac{\exp(\delta_{jyvt}) \exp(\bar{\delta}_{yvt} + d_v g_{iy})}{\sum_{\tilde{j} \in y} \exp(\delta_{\tilde{j}yvt})[1 + \sum_{\tilde{y} \in \mathcal{Y}} \exp(\bar{\delta}_{\tilde{y}vt} + d_v g_{i\tilde{y}})]}$$

Hence, aggregate quantity demanded in area y, time t, of drug v is:

$$q_{yvt} \approx \sum_{j \in \mathcal{J}_y} D_v \sum_{y_i} M_{y_i} \frac{\exp(\delta_{jyvt}) \exp(\bar{\delta}_{yvt} + d_v g_{iy})}{\sum_{\tilde{j} \in y} \exp(\delta_{\tilde{j}yvt})[1 + \sum_{\tilde{y} \in \mathcal{Y}} \exp(\bar{\delta}_{\tilde{y}vt} + d_v g_{i\tilde{y}})]}$$

A.2 Fighting game with no uncertainty

$$\begin{cases} \phi_j > \Phi + \phi_o & 0.5(F, NF) + 0.5(F, NF) \to \text{o exits} \to F_{j,o} = 0 \\ -\Phi < \phi_j - \phi_o \leq \Phi \;\&\; \pi_j^{NF} > \pi_j^d \;\&\; \pi_o^{NF} > \pi_o^d & 0.5(F, NF) + 0.5(NF, F) \to \textbf{ME} \to F_{j,o} = 0 \\ -\Phi < \phi_j - \phi_o \leq \Phi \;\&\; \pi_j^{NF} > \pi_j^d \;\&\; \pi_o^{NF} \leq \pi_o^d & 0.5(NF, F) + 0.5(NF, F) \to \text{j exits} \to F_{j,o} = 0 \\ -\Phi < \phi_j - \phi_o \leq \Phi \;\&\; \pi_j^{NF} \leq \pi_j^d \;\&\; \pi_o^{NF} > \pi_o^d & 0.5(F, NF) + 0.5(F, NF) \to \text{o exits} \to F_{j,o} = 0 \\ -\Phi < \phi_j - \phi_o \leq \Phi \;\&\; \pi_j^{NF} \leq \pi_j^d \;\&\; \pi_o^{NF} \leq \pi_o^d & 0.5(NF, F) + 0.5(F, NF) \to \textbf{ME} \to F_{j,o} = 0 \\ \phi_o > \Phi + \phi_j & 0.5(NF, F) + 0.5(NF, F) \to \text{j exits} \to F_{j,o} = 0 \end{cases}$$

A.3 Fighting game with uncertainty

$$
\begin{cases}
E\pi_j \leq \pi_j^{NF} \leq \pi_j^p \;\&\; E\pi_o \leq \pi_o^{NF} \leq \pi_o^p & 0.5(F,NF)+0.5(NF,F) \rightarrow \textbf{ME} \rightarrow \textbf{ME} \rightarrow F_{j,o}=0 \\
\pi_j^{NF} \leq E\pi_j \leq \pi_j^p \;\&\; E\pi_o \leq \pi_o^{NF} \leq \pi_o^p & 0.5(F,NF)+0.5(F,NF) \rightarrow \textbf{ME} \rightarrow \text{o exits} \rightarrow F_{j,o}=0 \\
\pi_j^{NF} \leq \pi_j^p \leq E\pi_j \;\&\; E\pi_o \leq \pi_o^{NF} \leq \pi_o^p & 0.5(F,NF)+0.5(F,NF) \rightarrow \textbf{ME} \rightarrow \text{o exits} \rightarrow F_{j,o}=0 \\
E\pi_j \leq \pi_j^{NF} \leq \pi_j^p \;\&\; \pi_o^{NF} \leq E\pi_o \leq \pi_o^p & 0.5(NF,F)+0.5(NF,F) \rightarrow \textbf{ME} \rightarrow \text{j exits} \rightarrow F_{j,o}=0 \\
\pi_j^{NF} \leq E\pi_j \leq \pi_j^p \;\&\; \pi_o^{NF} \leq E\pi_o \leq \pi_o^p & 0.5(NF,F)+0.5(F,NF) \rightarrow \text{nothing happens} \rightarrow F_{j,o}=0 \\
\pi_j^{NF} \leq \pi_j^p \leq E\pi_j \;\&\; \pi_o^{NF} \leq E\pi_o \leq \pi_o^p & 0.5(F,F)+0.5(F,NF) \rightarrow \textbf{ME} \rightarrow \text{fight} \rightarrow F_{j,o}=1 \\
E\pi_j \leq \pi_j^{NF} \leq \pi_j^p \;\&\; \pi_o^{NF} \leq \pi_o^p \leq E\pi_o & 0.5(NF,F)+0.5(NF,F) \rightarrow \textbf{ME} \rightarrow \text{j exits} \rightarrow F_{j,o}=0 \\
\pi_j^{NF} \leq E\pi_j \leq \pi_j^p \;\&\; \pi_o^{NF} \leq \pi_o^p \leq E\pi_o & 0.5(NF,F)+0.5(F,F) \rightarrow \textbf{ME} \rightarrow \text{fight} \rightarrow F_{j,o}=1 \\
\pi_j^{NF} \leq \pi_j^p \leq E\pi_j \;\&\; \pi_o^{NF} \leq \pi_o^p \leq E\pi_o & 0.5(F,F)+0.5(F,F) \rightarrow \text{fight} \rightarrow \text{fight} \rightarrow F_{j,o}=1
\end{cases}
$$

A.4 Multiple equilibria simplified game

$$
\begin{cases}
Pr(F_{jo}=1) = Pr(\pi_j^{NF} \leq \pi_j^p \leq E\pi_j \;\&\; \pi_o^{NF} \leq E\pi_o \leq \pi_o^p; \\
\quad \pi_j^{NF} \leq E\pi_j \leq \pi_j^p \;\&\; \pi_o^{NF} \leq \pi_o^p \leq E\pi_o; \pi_j^{NF} \leq \pi_j^p \leq E\pi_j \;\&\; \pi_o^{NF} \leq \pi_o^p \leq E\pi_o), \\
Pr(F_{jo}=0) = Pr(\pi_j^{NF} \leq E\pi_j \leq \pi_j^p \;\&\; \pi_o^{NF} \leq E\pi_o \leq \pi_o^p; \\
\quad E\pi_j \leq \pi_j^{NF} \leq \pi_j^p \;\&\; \pi_o^{NF} \leq E\pi_o \leq \pi_o^p; E\pi_j \leq \pi_j^{NF} \leq \pi_j^p \;\&\; \pi_o^{NF} \leq \pi_o^p \leq E\pi_o; \\
\quad \pi_j^{NF} \leq E\pi_j \leq \pi_j^p \;\&\; E\pi_o \leq \pi_o^{NF} \leq \pi_o^p; \pi_j^{NF} \leq \pi_j^p \leq E\pi_j \;\&\; E\pi_o \leq \pi_o^{NF} \leq \pi_o^p; \\
\quad E\pi_j \leq \pi_j^{NF} \leq \pi_j^p \;\&\; E\pi_o \leq \pi_o^{NF} \leq \pi_o^p)
\end{cases}
\tag{10}
$$

A.5 Identification and estimation demand

Consider the across-areas unconditional demand function:

$$log(q^*_{yvt}) = \alpha p_{vt} + \mu_m F_{ytm} + f_t + f_y + f_v + \xi_{yvt}$$

We can see this process as a system of two equations:

$$q^*_{yvt} = d(p_{vt}, F_{ytm}, \boldsymbol{\xi})$$
$$Q_{yvt} = q^*_{yvt} s(O_{yt}, \epsilon_{ytv})$$

where ϵ_{ijv} are other characteristics affecting seizure rates, potentially correlated with demand

and/or determinants of the market. Taking logarithms, assuming additive separability, and substituting the first equation in the second:

$$ln(Q_{yvt}) = \alpha p_{vt} + \mu_m F_{ytm} + f_t + f_y + f_v + \xi_{yvt} + ln(s(O_{yt})) + ln(s(\epsilon_{ytv}))$$

Now, while it is reasonable to assume $\mathbb{E}[F_{ytm}\xi_{yvt}] = 0$ and $\mathbb{E}[F_{ytm}ln(s(\epsilon_{ytv}))] = 0$, the endogeneity concern arise from $\mathbb{E}[F_{ytm}ln(s(O_{yt}))] \neq 0$. In other words, without a way to control for the change in seizure rate, driven by the change in police attention, μ_m is not identified. We need an additional equation. Let's specify an equation for the number of drug seizures–which proxies for the seizure selection:

$$N_{ytv} = k(O_{yt}, q^*_{yvt}, \epsilon_{ytv}) = k(O_{yt}, p_{vt}, F_{ytm}, \boldsymbol{\xi}, \epsilon_{ytv})$$

Notice that simply controlling for N_{ytv} will give us wrong estimates too. Why? By doing so, we are not only controlling for the increase in seizures due to the increase in attention ΔO_{yt}, but also the decrease in seizure driven by the decrease in quantity $\Delta ln(k(q^*_{yvt}))$. Therefore, it is unclear what the resulting parameter would identify. Instead, we want to control only for changes in selection $\Delta ln(N_{ytv})$ driven by changes in police attention ΔO_{yt}. Hence: $\Delta ln(\hat{N}_{ytv})$. Assuming (log) additive separability:

$$ln(N_{ytv}) \approx kO_{yt} + ln(k(p_{vt})) + ln(k(F_{ytm})) + \underbrace{ln(k(\boldsymbol{\xi}) + ln(k(\epsilon_{ytv}))}_{u_{yvt}}$$

Under exogeneity $\mathbb{E}[O_{yt}u_{yvt}] = 0$, we can consistently estimate k. Here we start to understand the crucial role of the measure of police attention chosen. This has to be excluded from q^*_{yvt}, since we need $\mathbb{E}[O_{yt}ln(k(\boldsymbol{\xi}))] = 0$. Let's use the number of arrests by the local police as IV, for the reason detailed in section 5:

$$log(N_{yvt}) \approx kA_{yt} + \gamma_1 p_{vt} + \gamma_2 F_{yt} + u_{yvt} \rightarrow log(\hat{N}_{ytv}) = \hat{\eta} A_{yt}$$

Under the assumption that:

$$\Delta ln(s(O_{yt})) = \Delta ln(\hat{N}_{ytv})$$

we can rewrite:

$$ln(Q_{yvt}) = \alpha p_{vt} + \mu_m F_{ytm} + \gamma ln(\hat{N}_{ytv}) + f_t + f_y + f_v + \xi_{yvt} + ln(s(\epsilon_{ytv}))$$

And we have identification under the conditional parallel trend assumption by usual OLS. To simplify notation, denote by $\epsilon_{ytv} = ln(s(\epsilon_{ytv}))$:

$$ln(Q_{yvt}) = \alpha p_{vt} + \mu_m F_{ytm} + \gamma ln(\hat{N}_{ytv}) + f_t + f_y + f_v + \xi_{yvt} + \epsilon_{ytv}$$

Summing up, we mainly need the two following assumptions to reach identification:

Assumption - Exclusion restriction. $\mathbb{E}[A_{yt}(\xi_{yvt} + \epsilon_{ytv})] = 0$

Assumption - Conditional parallel trend. $\mathbb{E}[F_{yt}(\xi_{yvt} + \epsilon_{ytv})|\hat{N}_{yt}] = 0$

B Additional figures

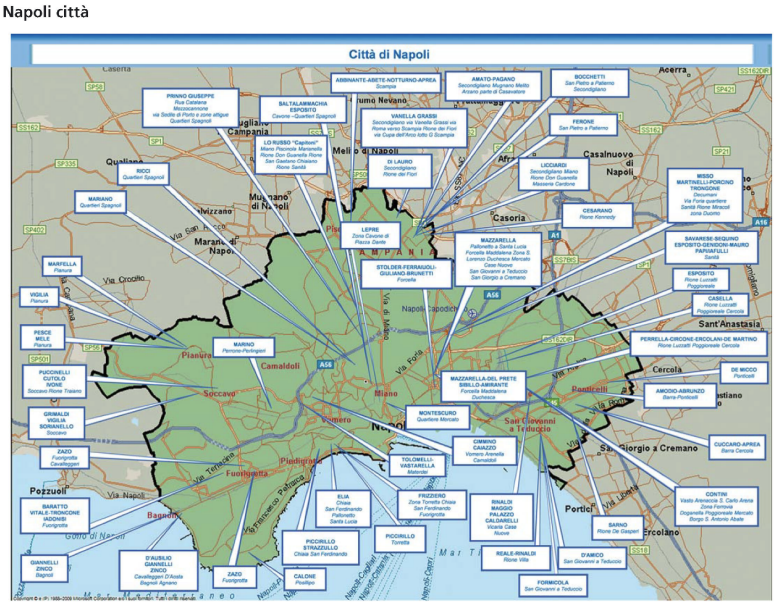
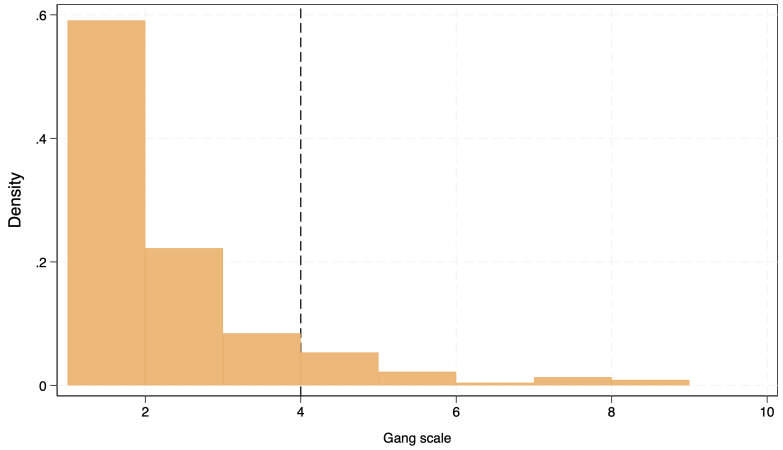


Figure A1: DIA report - map ← Return to text

I SALTALAMACCHIA-ESPOSITO si starebbero, così, spingendo verso le vicine aree del Cavone, della Pignasecca, di Montesanto e della zona Porto, cosa che potrebbe innescare contrasti con il *clan* ELIA, presente nell'adiacente area del Pallonetto Santa Lucia.

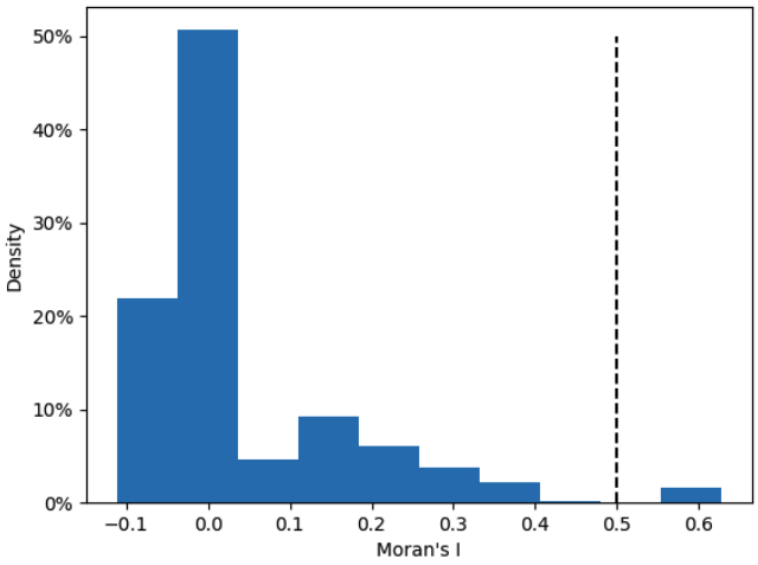
Nella zona Porto si registra il ritorno di esponenti della *famiglia* PRINNO, originaria di Rua Catalana, che avrebbero approfittato del "vuoto di potere" determinato dallo stato di detenzione di quasi tutti gli affiliati ad un altro

Figure A2: DIA report - text ← Return to text



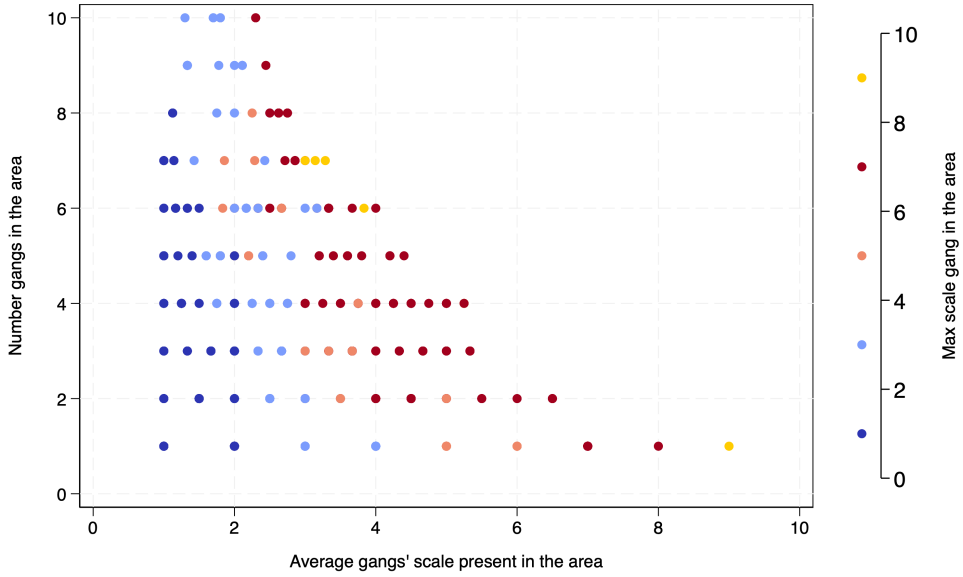
Notes: This figure presents the distribution of gang scale in the data. The scale of a gang, in a given year, is the number of locations in which it is present.

Figure A3: Density gang scale ← Return to text



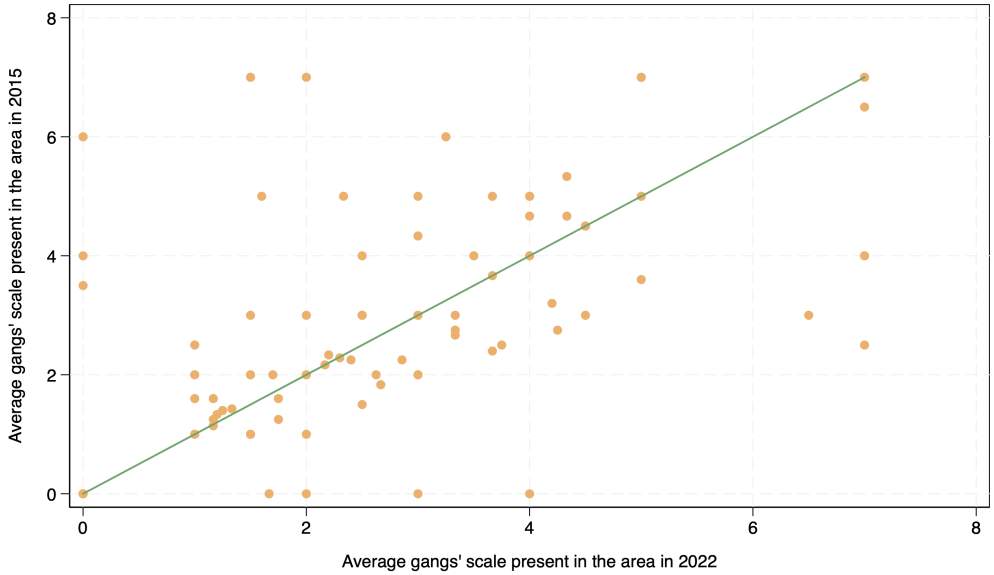
Notes: This figure presents the Moran's I index of spatial concentration of gangs spatial distribution. The vertical line indicates 0.5, the rule of thumb for spatial concentration.

Figure A4: Moran's I ← Return to text



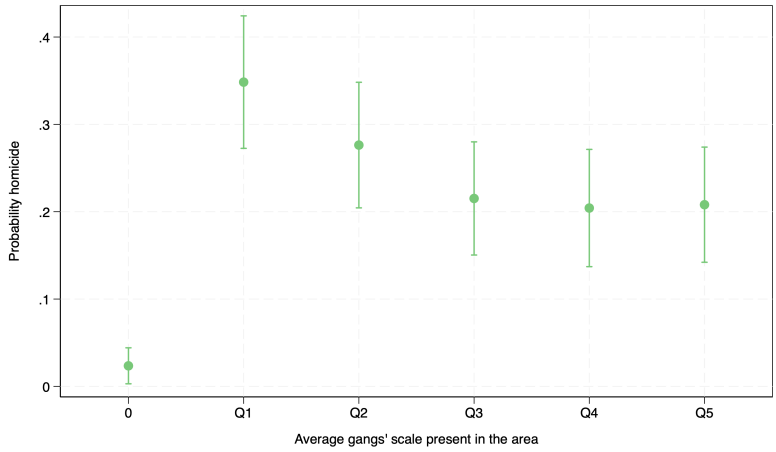
Notes: This figure presents cross-sectional variation in gangs presence. Each dot is a location-year (location is a district within Naples, and a city in the province).

Figure A5: Cross section variation in gang scale ← Return to text



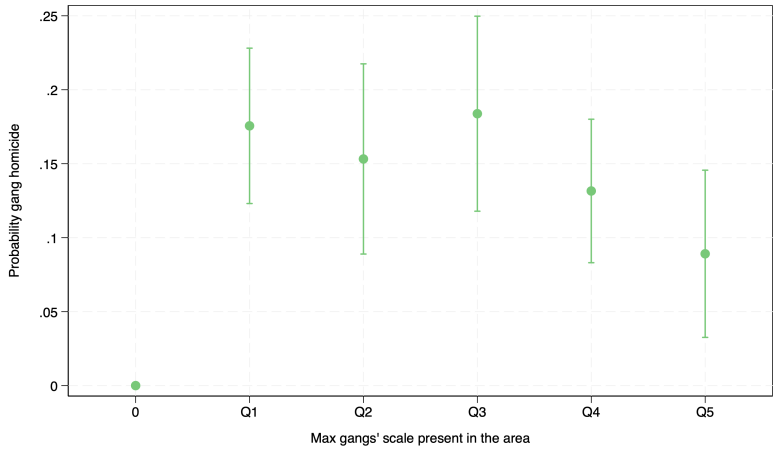
Notes: This figure presents cross-sectional variation in gangs presence. Each dot is a location-year (location is a district within Naples, and a city in the province).

Figure A6: Time variation in gang scale ← Return to text



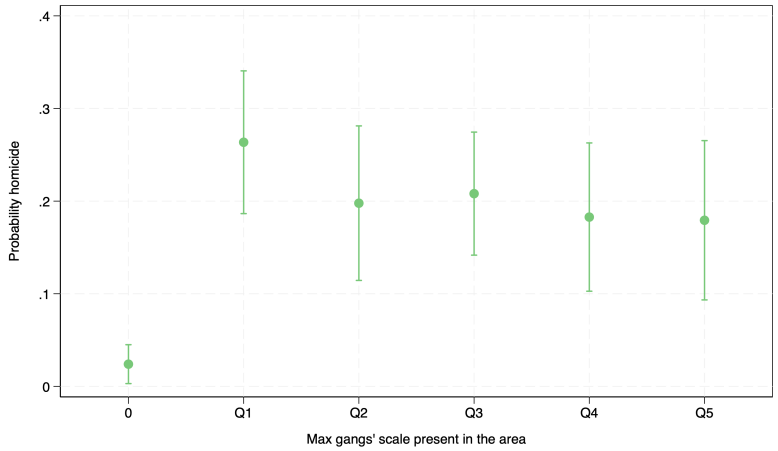
Notes: This figure presents the average probability of homicides for locations-years with no gangs, and for the five quintiles of the average scale of gangs present in the area distribution. The scale of a gang, in a given year, is the number of locations in which it is present.

Figure A7: Prob. homicide by mean scale ← Return to text



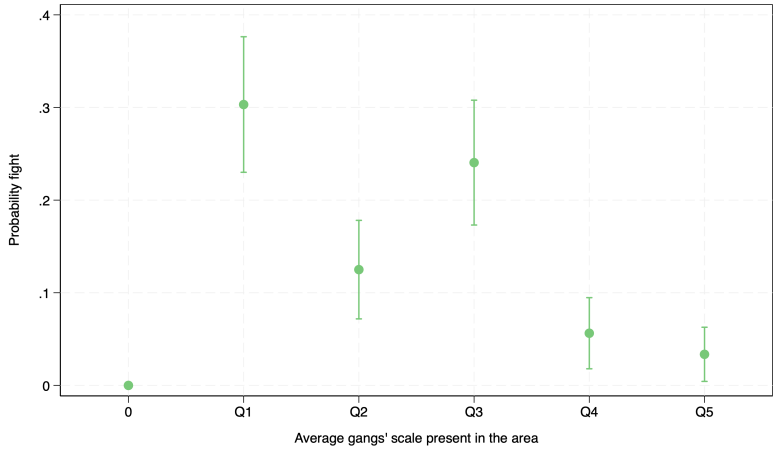
Notes: This figure presents the average probability of gang homicides for locations-years with no gangs, and for the five quintiles of max scale of gangs present in the area distribution. An homicide is coded as gang homicide if there was any gang mentioning on the internet related to the homicide. The scale of a gang, in a given year, is the number of locations in which it is present.

Figure A8: Prob. gang homicide by max scale ← Return to text



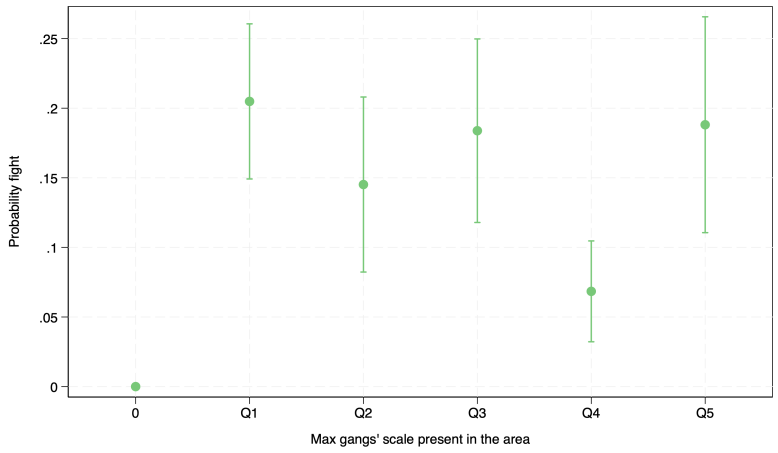
Notes: This figure presents the average probability of homicides for locations-years with no gangs, and for the five quintiles of the max scale of gangs present in the area distribution. The scale of a gang, in a given year, is the number of locations in which it is present.

Figure A9: Prob. homicide by max scale ← Return to text



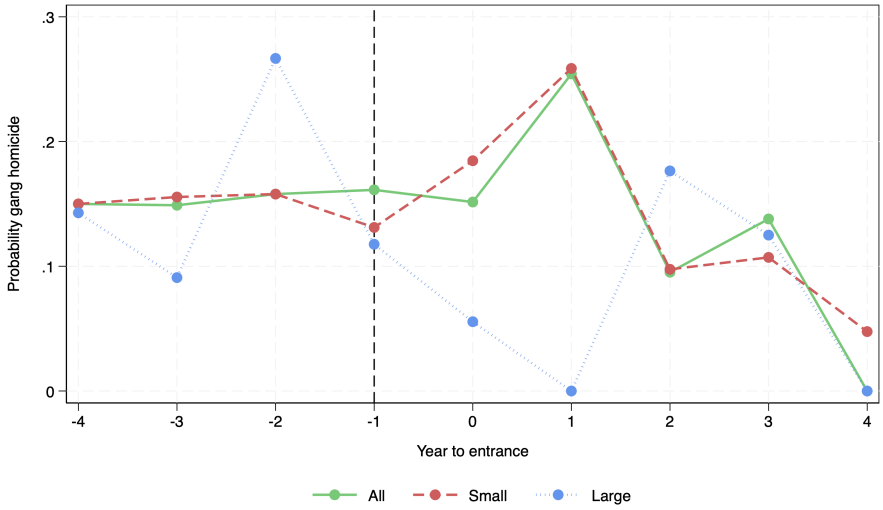
Notes: This figure presents the average probability of fight for locations-years with no gangs, and for the five quintiles of the mean f scale of gangs present in the area distribution. The scale of a gang, in a given year, is the number of locations in which it is present.

Figure A10: Prob. fight by mean scale ← Return to text



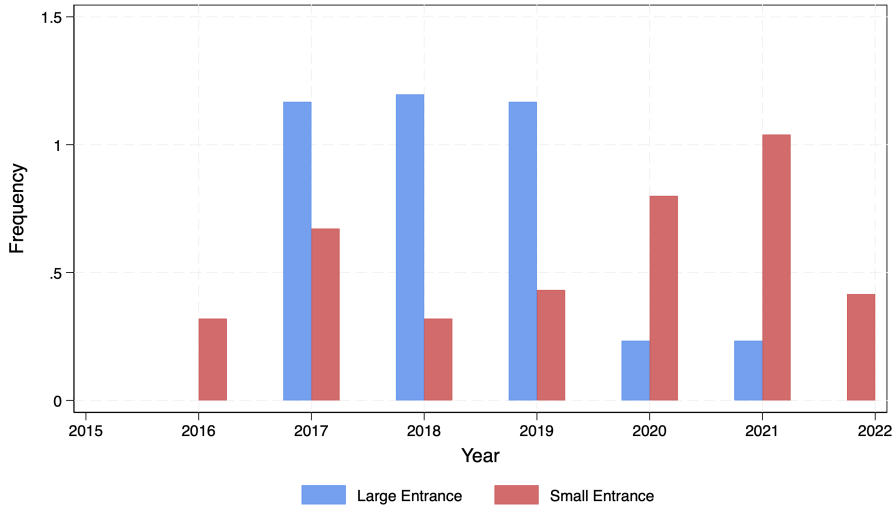
Notes: This figure presents the average probability of fight for locations-years with no gangs, and for the five quintiles of the max scale of gangs present in the area distribution. The scale of a gang, in a given year, is the number of locations in which it is present.

Figure A11: Prob. war by max scale ← Return to text



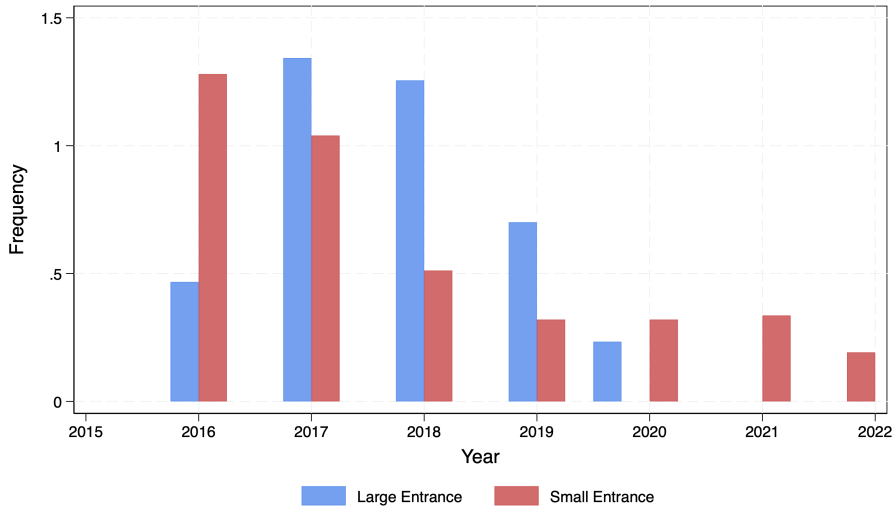
Notes: This figure presents the average probability of gang homicides for locations-years relative to the last entry of a new gang in the area, separately for a general entry, the entry of a small gang, and the entry of a large gang. An homicide is coded as gang homicide if there was any gang mentioning on the internet related to the homicide. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. A gang is defined to entry in an area at time t if is present in the area at t, but not in $t-1$.

Figure A12: Event study - probability gang homicide, raw data ← Return to text



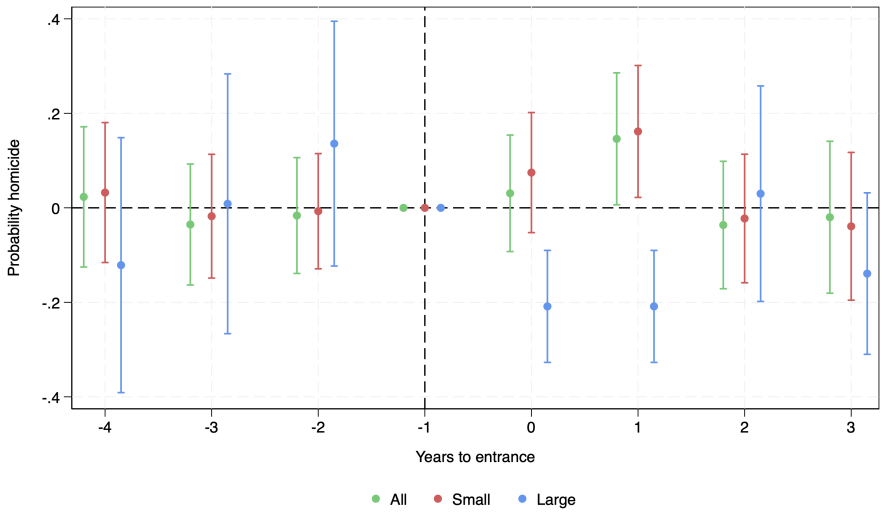
Notes: This figure presents the frequency of last entry in an area, separately for large and small gangs. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. A gang is defined to entry in an area at time t if is present in the area at t, but not in $t-1$.

Figure A13: Event study - variation entrance ← Return to text



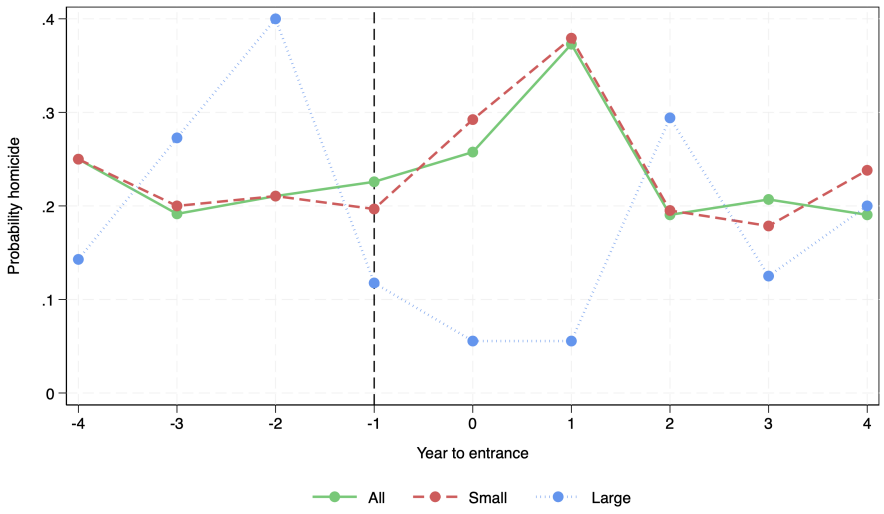
Notes: This figure presents the frequency of first entry in an area, separately for large and small gangs. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. A gang is defined to entry in an area at time t if is present in the area at t, but not in $t-1$.

Figure A14: Event study - variation entrance, first entry ← Return to text



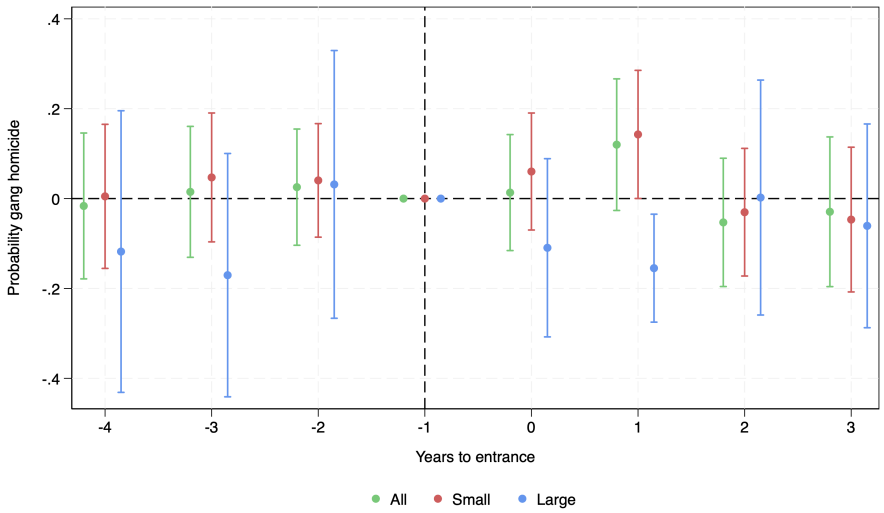
Notes: This figure presents the event-study coefficients separately for the last entry of a new gang in the area, the last entry of a small gang, and the last entry of a large gang, on the probability of homicide. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. A gang is defined to entry in an area at time t if is present in the area at t, but not in $t-1$. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown. Standard errors clustered at the location level (district within Naples, city in the province).

Figure A15: Event study - probability homicide ← Return to text



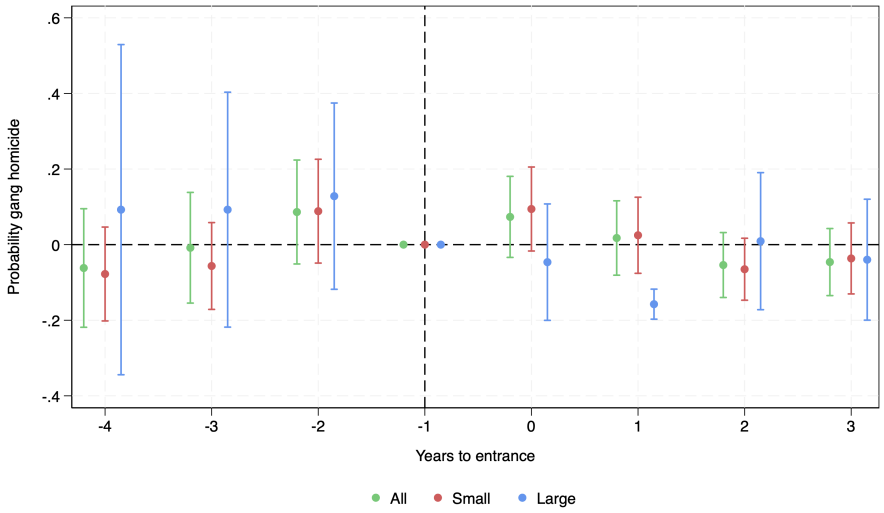
Notes: This figure presents the average probability of homicides for locations-years relative to the last entry of a new gang in the area, separately for a general entry, the entry of a small gang, and the entry of a large gang. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. A gang is defined to entry in an area at time t if is present in the area at t, but not in $t-1$.

Figure A16: Event study - probability homicide, raw data ← Return to text



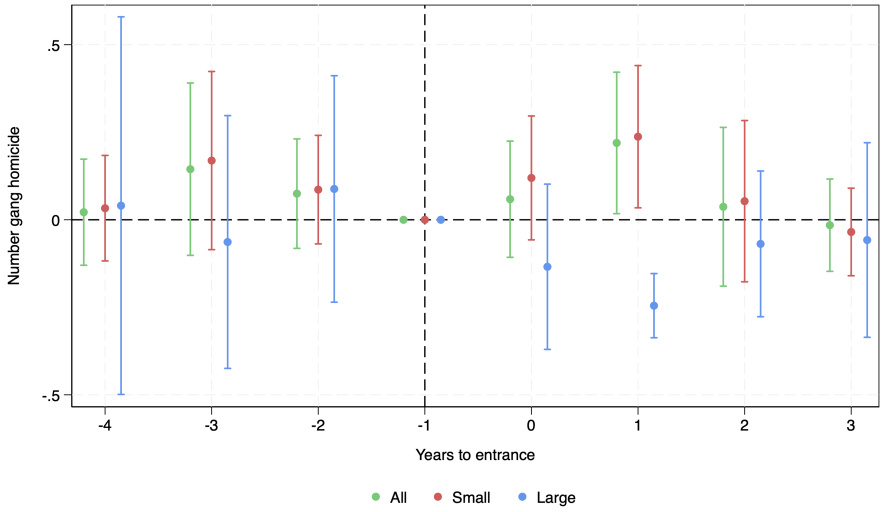
Notes: This figure presents the event-study coefficients separately for the last entry of a new gang in the area, the last entry of a small gang, and the last entry of a large gang, on the probability of gang homicide. An homicide is coded as gang homicide if there was any gang mentioning on the internet related to the homicide. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. A gang is defined to entry in an area at time t if is present in the area at t, but not in $t-1$. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown. Standard errors clustered at the location level (district within Naples, city in the province). Location and year fixed effects included in the model.

Figure A17: Event study - probability gang homicide, fixed effects ← Return to text



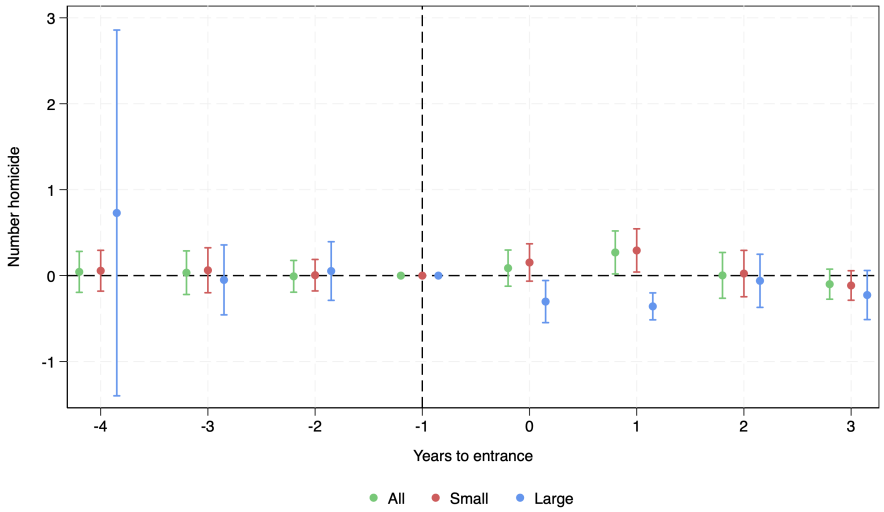
Notes: This figure presents the event-study coefficients separately for the first entry of a new gang in the area, the first entry of a small gang, and the first entry of a large gang, on the probability of gang homicide. An homicide is coded as gang homicide if there was any gang mentioning on the internet related to the homicide. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. A gang is defined to entry in an area at time t if is present in the area at t, but not in $t-1$. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown. Standard errors clustered at the location level (district within Naples, city in the province).

Figure A18: Event study - probability gang homicide, first entry ← Return to text



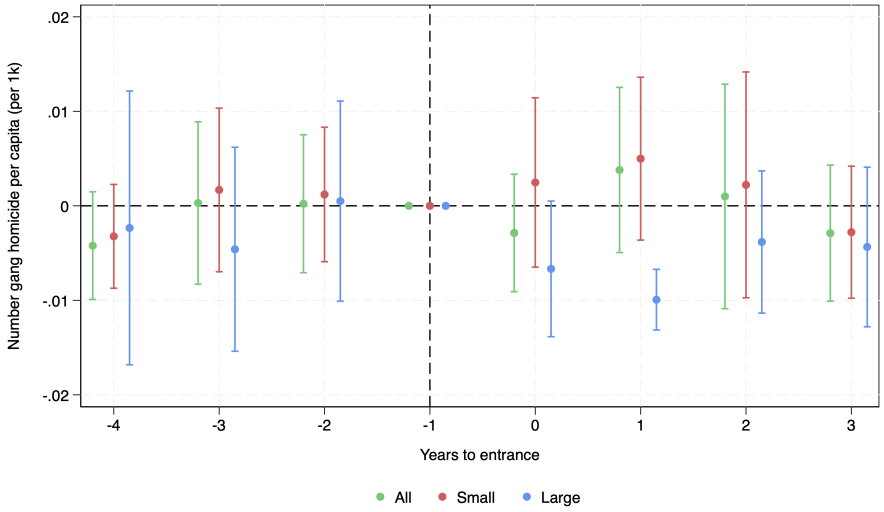
Notes: This figure presents the event-study coefficients separately for the last entry of a new gang in the area, the last entry of a small gang, and the last entry of a large gang, on the number of gang homicides. An homicide is coded as gang homicide if there was any gang mentioning on the internet related to the homicide. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. A gang is defined to entry in an area at time t if is present in the area at t, but not in $t-1$. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown. Standard errors clustered at the location level (district within Naples, city in the province).

Figure A19: Event study - number gang homicides ← Return to text



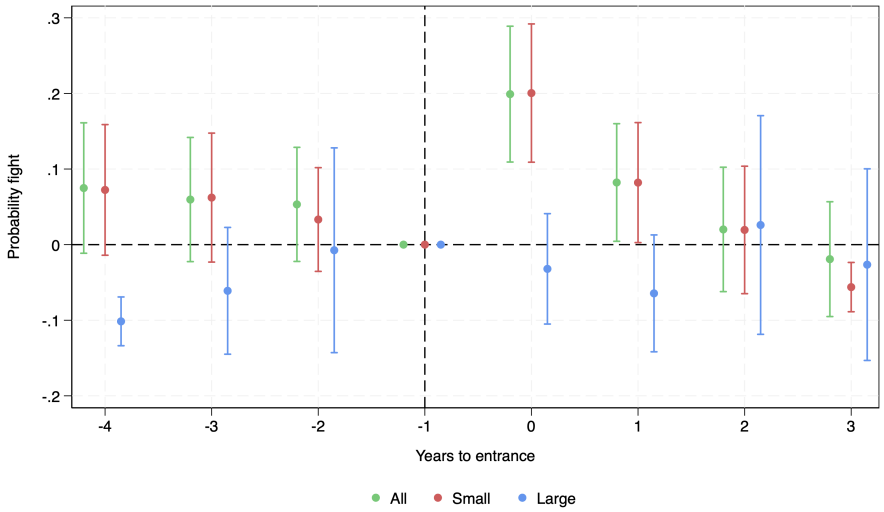
Notes: This figure presents the event-study coefficients separately for the last entry of a new gang in the area, the last entry of a small gang, and the last entry of a large gang, on the number of homicides. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. A gang is defined to entry in an area at time t if is present in the area at t, but not in $t-1$. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown. Standard errors clustered at the location level (district within Naples, city in the province).

Figure A20: Event study - number homicides ← Return to text



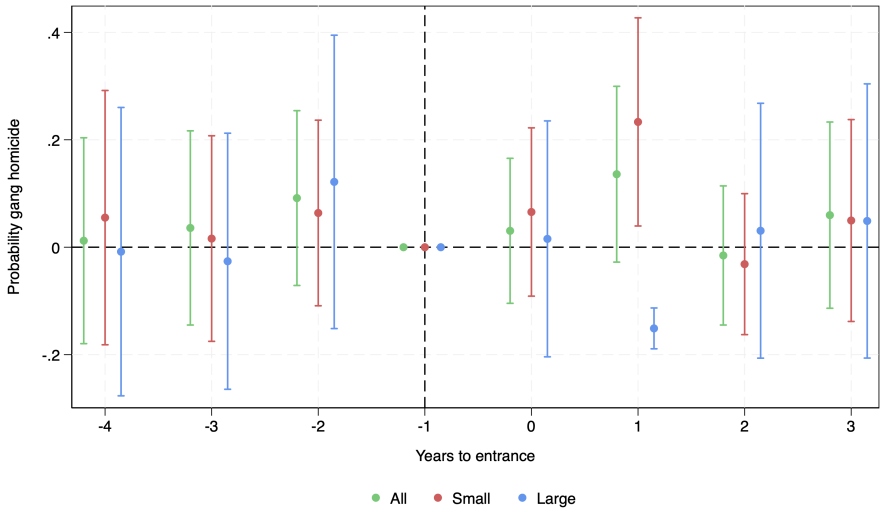
Notes: This figure presents the event-study coefficients separately for the last entry of a new gang in the area, the last entry of a small gang, and the last entry of a large gang, on the number of gang homicides per 1k people living in the area. An homicide is coded as gang homicide if there was any gang mentioning on the internet related to the homicide. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. A gang is defined to entry in an area at time t if is present in the area at t, but not in $t-1$. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown. Standard errors clustered at the location level (district within Naples, city in the province).

Figure A21: Event study - number gang homicides per capita ← Return to text



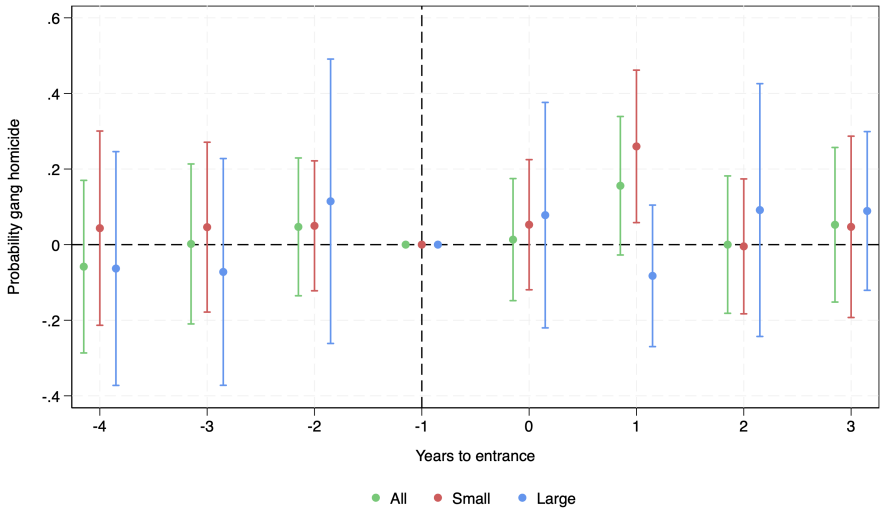
Notes: This figure presents the event-study coefficients separately for the last entry of a new gang in the area, the last entry of a small gang, and the last entry of a large gang, on the probability of fight in the area. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. A gang is defined to entry in an area at time t if is present in the area at t, but not in $t-1$. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown. Standard errors clustered at the location level (district within Naples, city in the province).

Figure A22: Event study - probability fight ← Return to text



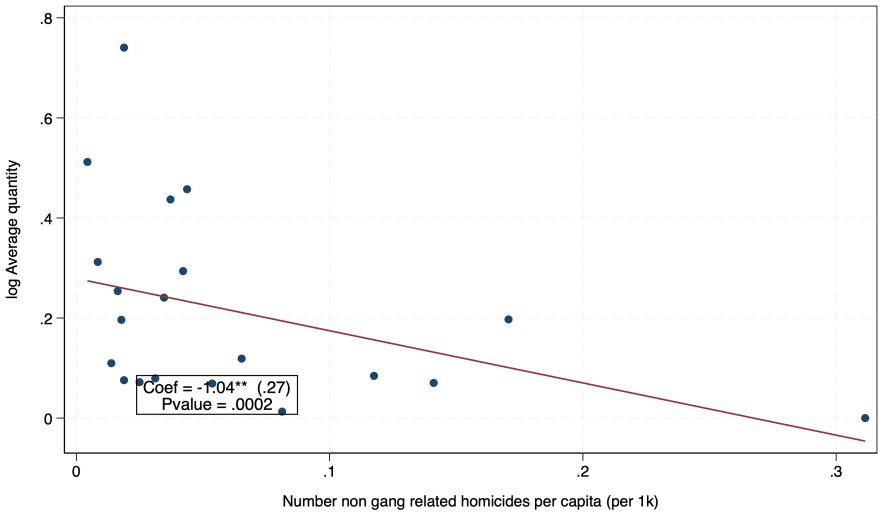
Notes: This figure presents the event-study coefficients separately for the last predicted entry of a new gang in the area, the last predicted entry of a small gang, and the last predicted entry of a large gang, on the probability of gang homicide. An homicide is coded as gang homicide if there was any gang mentioning on the internet related to the homicide. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. A gang is defined to entry in an area at time t if is present in the area at t, but not in $t-1$. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown. Standard errors clustered at the location level (district within Naples, city in the province). Entries are predicted with the IV described in section 3.

Figure A23: Event study - probability gang homicide, IV ← Return to text



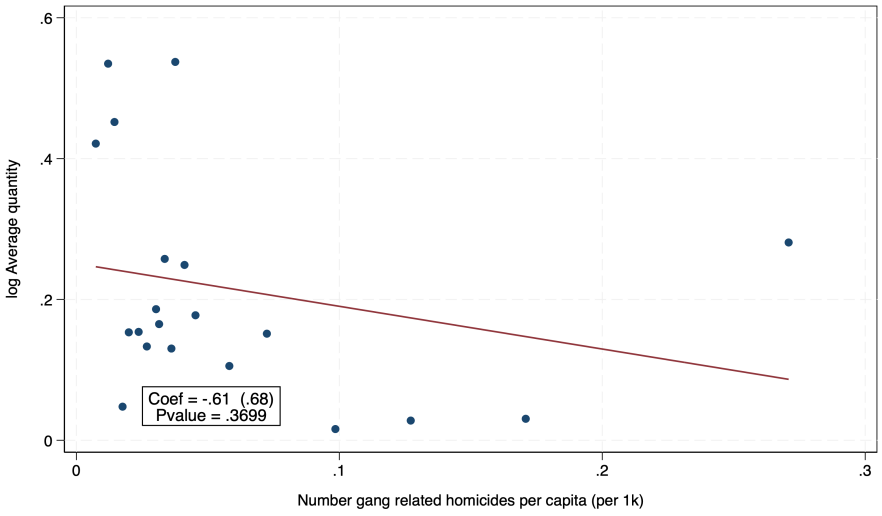
Notes: This figure presents the event-study coefficients separately for the last predicted entry of a new gang in the area, the last predicted entry of a small gang, and the last predicted entry of a large gang, on the probability of gang homicide. An homicide is coded as gang homicide if there was any gang mentioning on the internet related to the homicide. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. A gang is defined to entry in an area at time t if is present in the area at t, but not in $t-1$. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown. Standard errors clustered at the location level (district within Naples, city in the province). Entries are predicted with the IV described in section 3. Location and year fixed effects included in the model.

Figure A24: Event study - probability gang homicide, IV and fixed effects ← Return to text



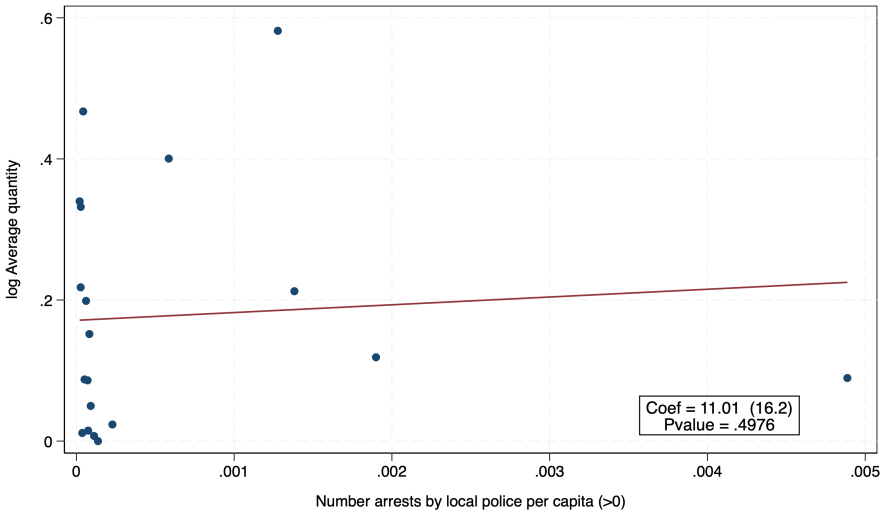
Notes: This figure presents scatter plot and linear fit of the log average quantity of drug seized in an area, in a given year, for a given drug, with the number of non gang homicides per 1k people living in the area. We exclude observations with 0 homicides for graphical purposes.

Figure A25: Correlation average quantity and non-gang homicide per capita ← Return to text



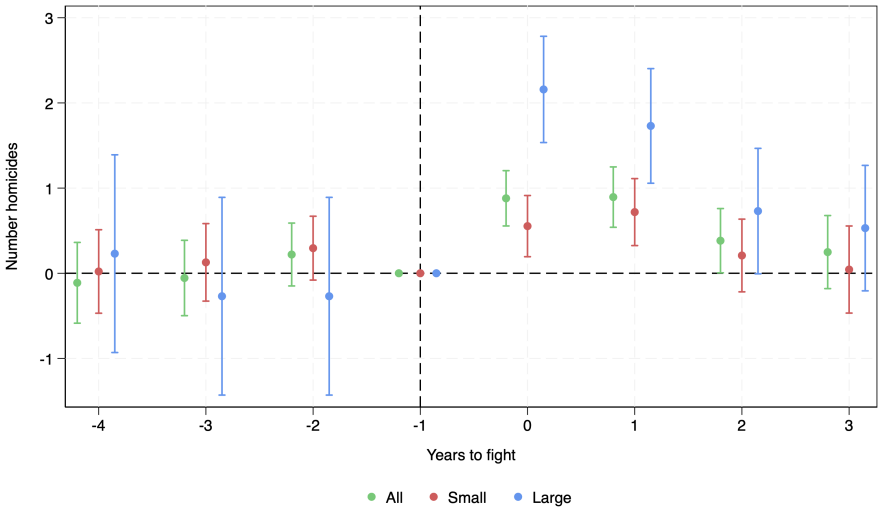
Notes: This figure presents scatter plot and linear fit of the log average quantity of drug seized in an area, in a given year, for a given drug, with the number of gang homicides per 1k people living in the area. We exclude observations with 0 homicides for graphical purposes.

Figure A26: Correlation average quantity and gang homicide per capita ← Return to text



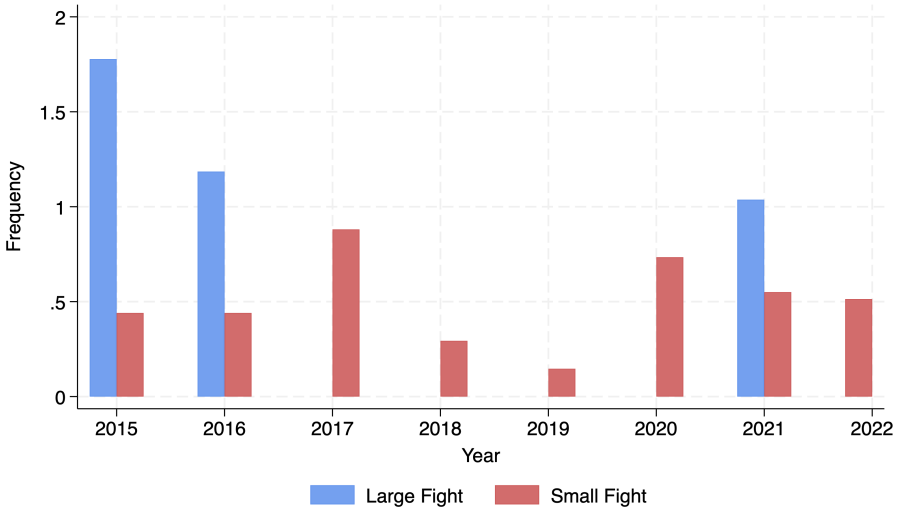
Notes: This figure presents scatter plot and linear fit of the log average quantity of drug seized in an area, in a given year, for a given drug, with the number of arrests by local police per capita. We exclude observations with 0 arrests for graphical purposes.

Figure A27: Correlation average quantity and number of arrests by local police per capita ← Return to text



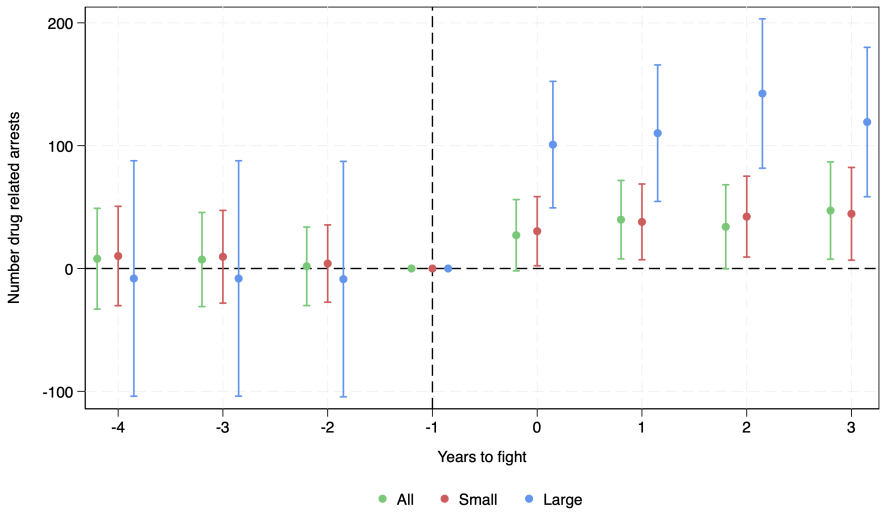
Notes: This figure presents the event-study coefficients separately for the general first fight, the first fight involving only small gangs, and the first fight involving at least one large gang, on the number of homicides in the area. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown.

Figure A28: Event study - number homicides ← Return to text



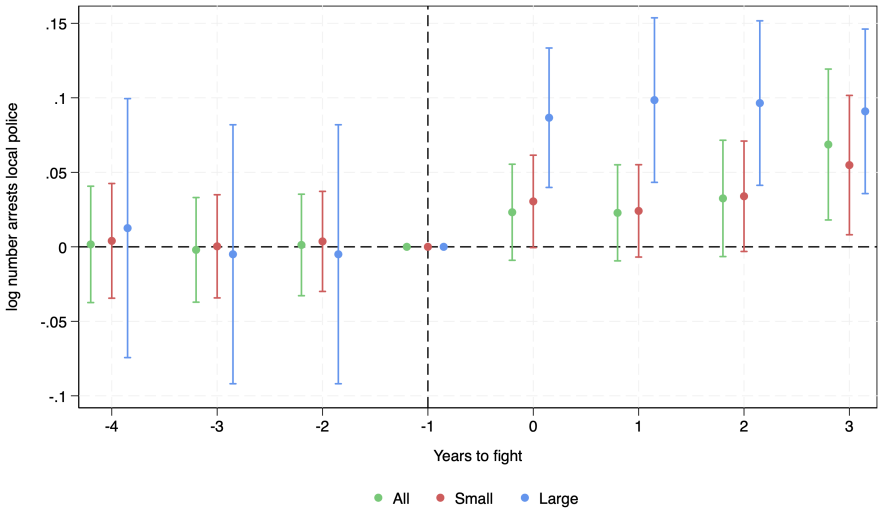
Notes: This figure presents the frequency of first fight in an area, separately for large and small gangs. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present.

Figure A29: Variation event-study fights ← Return to text



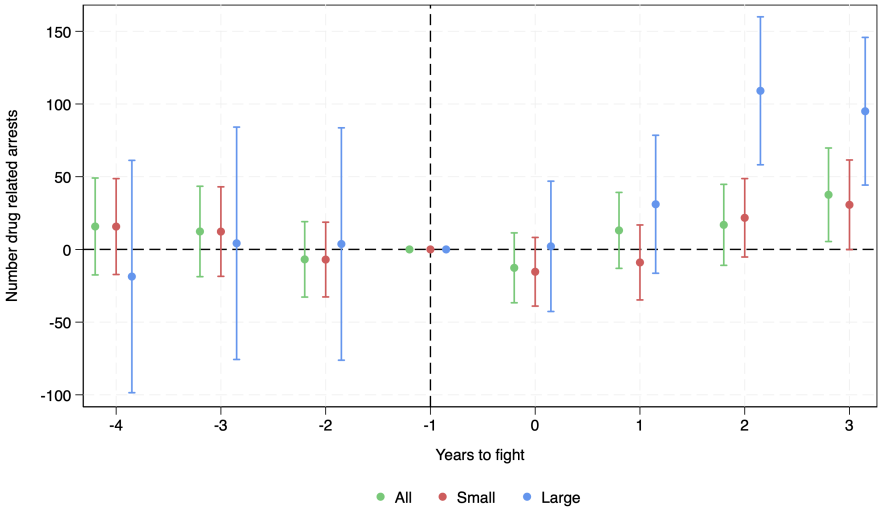
Notes: This figure presents the event-study coefficients separately for the general first fight, the first fight involving only small gangs, and the first fight involving at least one large gang, on the number of drug related arrests in the area. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown.

Figure A30: Event study - number of drug related arrests ← Return to text



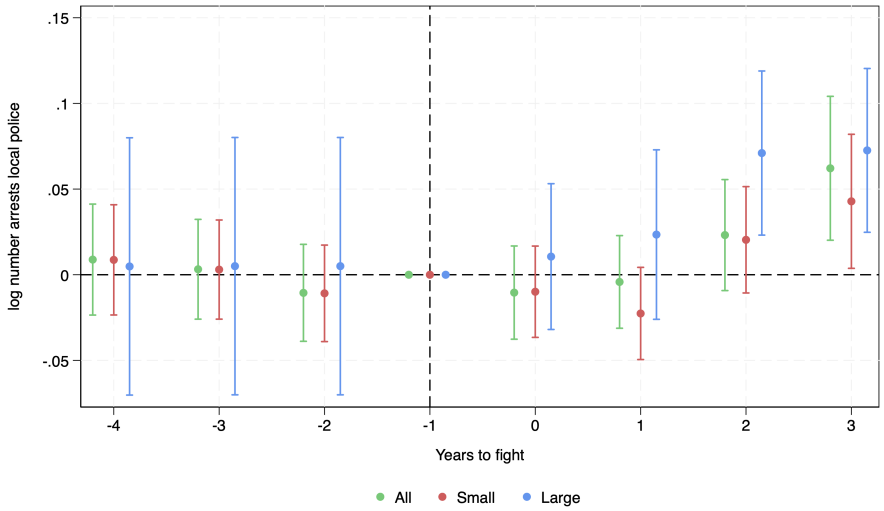
Notes: This figure presents the event-study coefficients separately for the general first fight, the first fight involving only small gangs, and the first fight involving at least one large gang, on the log number of arrests by local police in the area. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown.

Figure A31: Event study - number of arrests by local police ← Return to text



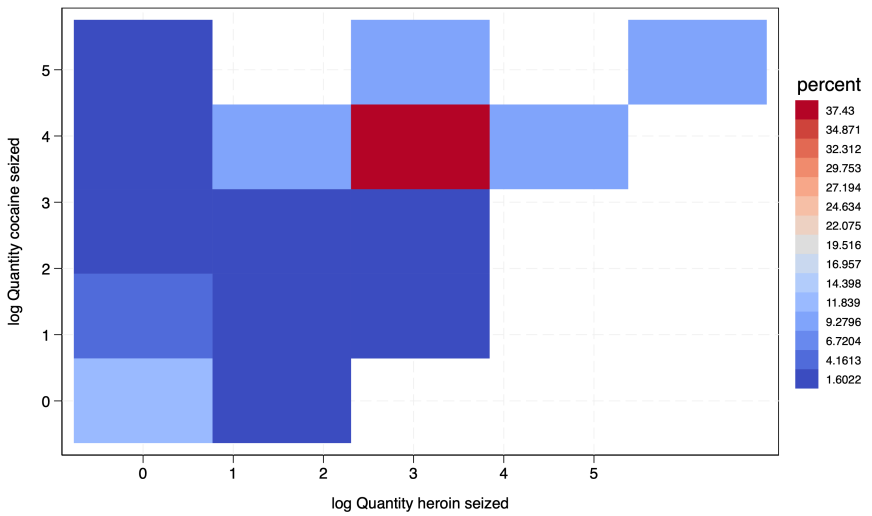
Notes: This figure presents the event-study coefficients separately for the general first fight, the first fight involving only small gangs, and the first fight involving at least one large gang, on the number of drug related arrests in the area controlling for the number of homicides. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown.

Figure A32: Event study - number of drug arrests, controlling for number of homicides ← Return to text



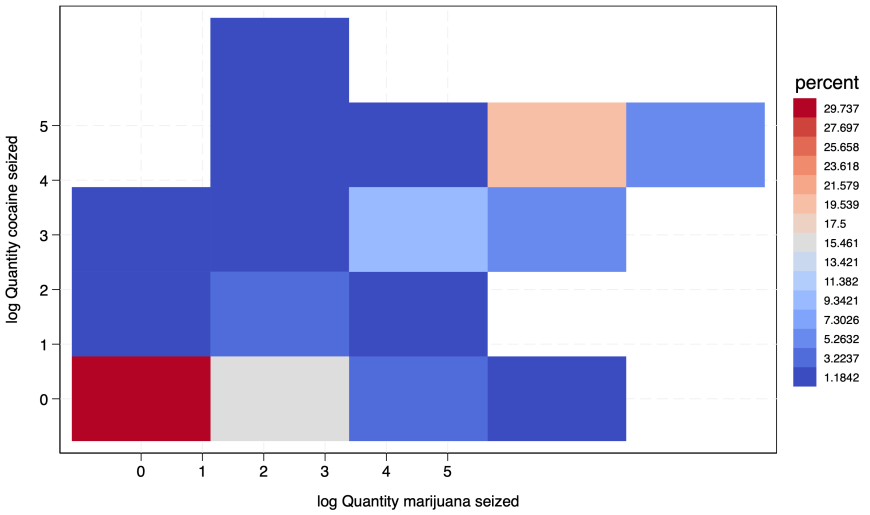
Notes: This figure presents the event-study coefficients separately for the general first fight, the first fight involving only small gangs, and the first fight involving at least one large gang, on the log number of arrests by local police in the area, controlling for the number of homicides. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. EVENTDD estimates Clarke & Tapia Schythe, 2023. 95% confidence interval shown.

Figure A33: Event study - number of arrests by local police, controlling for number of homicides
← Return to text



Notes: This figure presents the percent of location-year for log quantity of cocaine seized and log quantity of heroin seized.

Figure A34: Heatplot - seizures cocaine and heroin ← Return to text



Notes: This figure presents the percent of location-year for log quantity of cocaine seized and log quantity of heroin seized.

Figure A35: Heatplot - seizures cocaine and marijuana ← Return to text

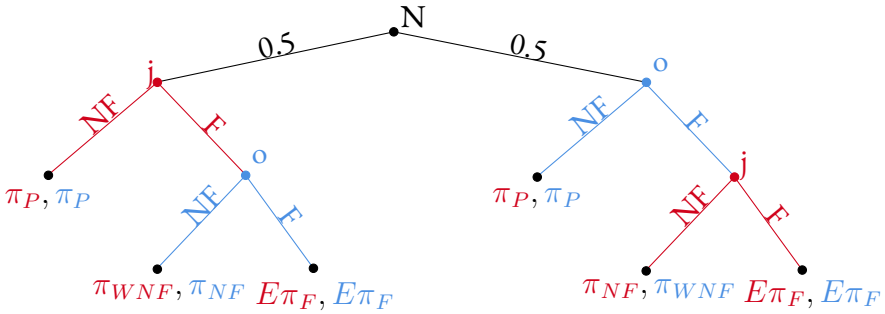


Figure A36: Fighting game ← Return to text

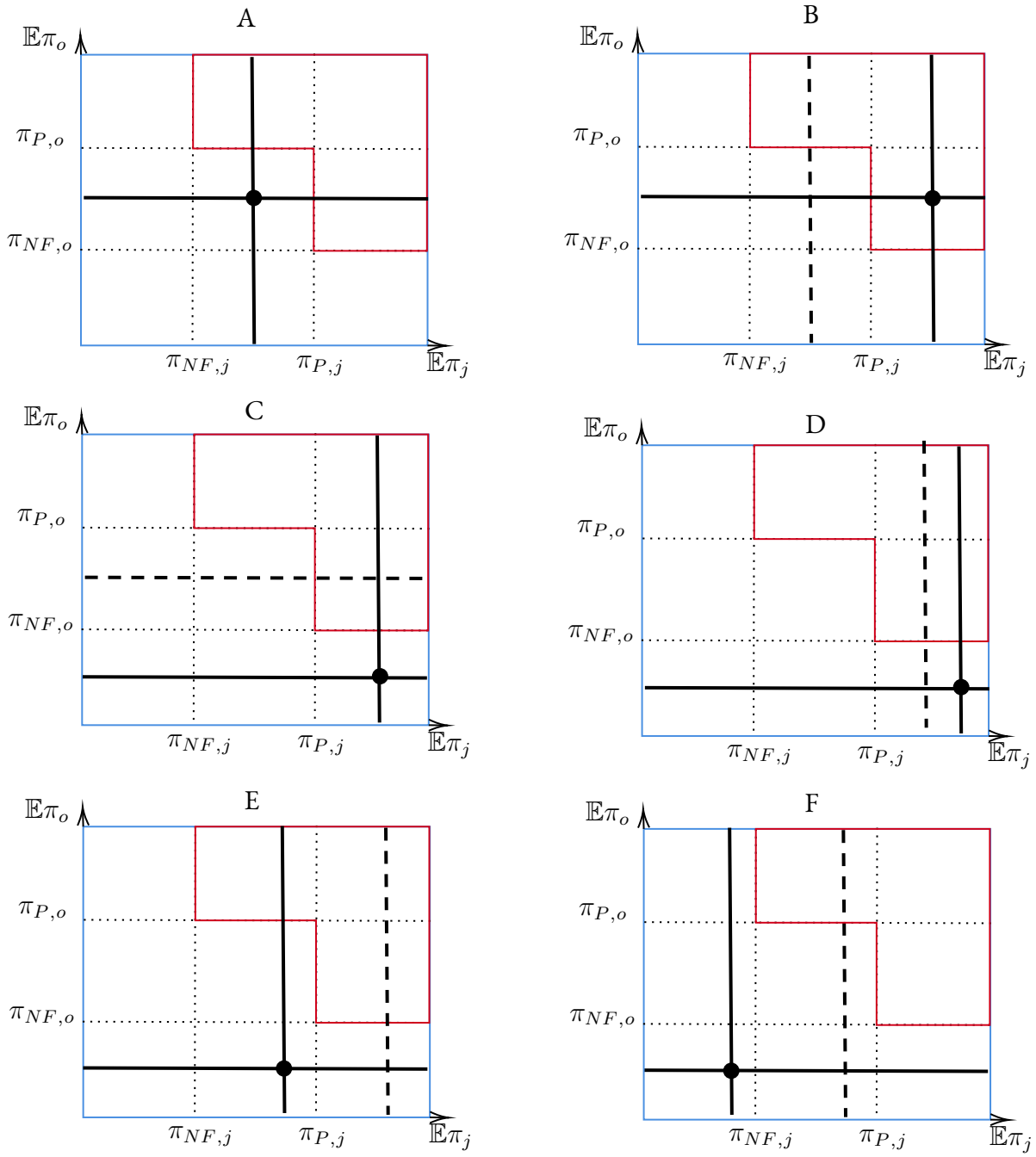
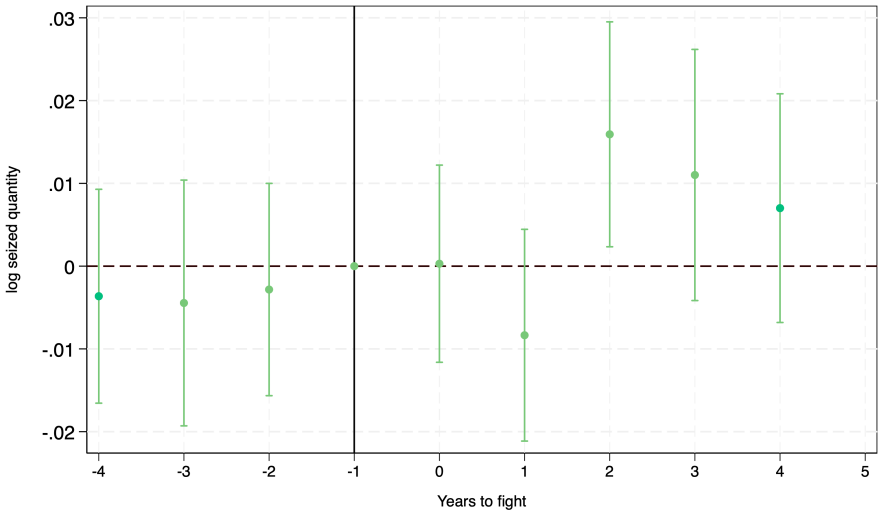
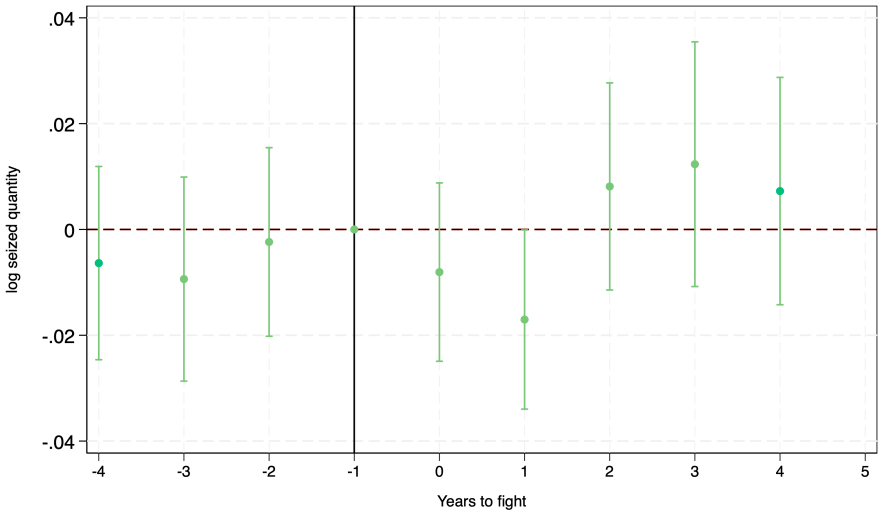


Figure A37: Theoretical results ← Return to text



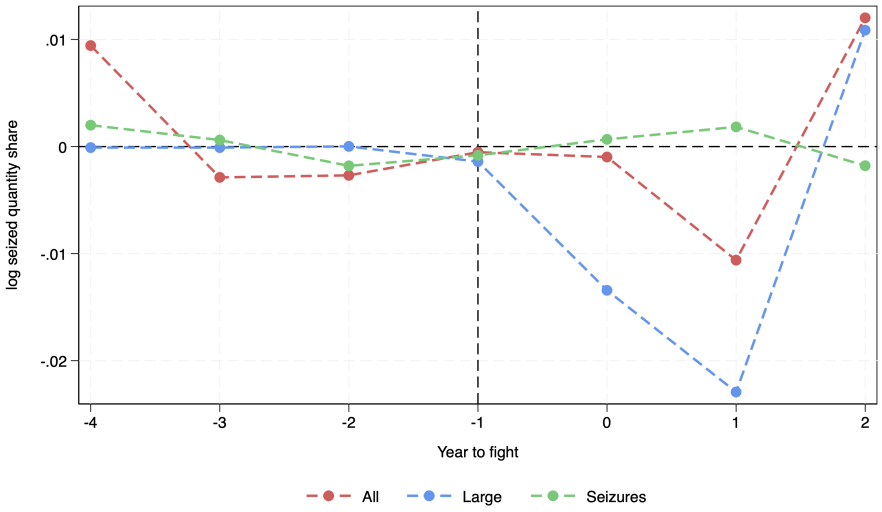
Notes: This figure presents the event-study coefficients for the first fight in the area on the log seized quantity. EVENTDD estimates Clarke & Tapia Schythe, 2023. 90% confidence interval shown. City, year, and type of drug fixed effects included in the model.

Figure A38: Event study - seized quantity ← Return to text



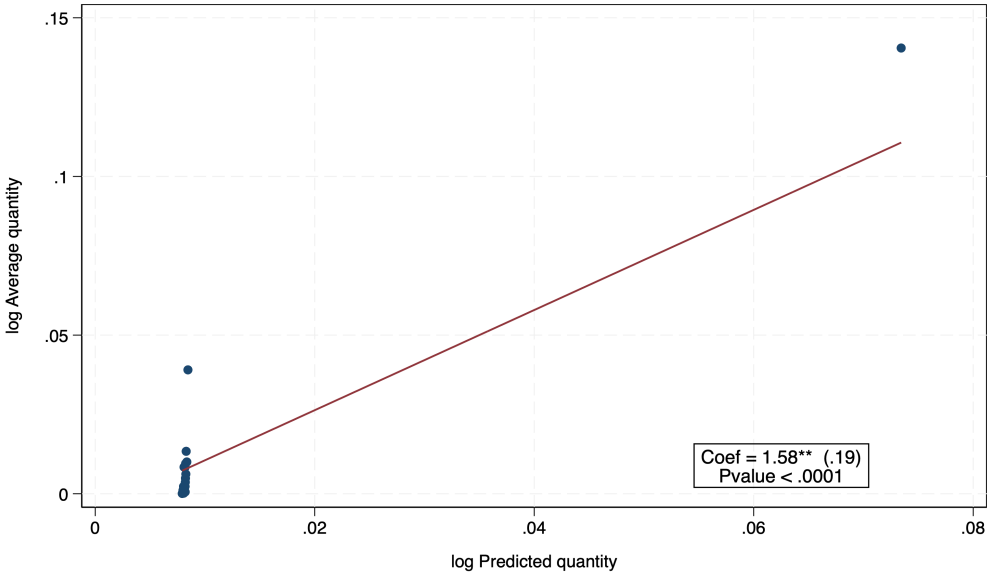
Notes: This figure presents the event-study coefficients for the first fight in the area on the log seized quantity controlling for selection. Additional information in Section 5. EVENTDD estimates Clarke & Tapia Schythe, 2023. 90% confidence interval shown. City, year, and type of drug fixed effects included in the model.

Figure A39: Event study - seized quantity, controlling for selection ← Return to text



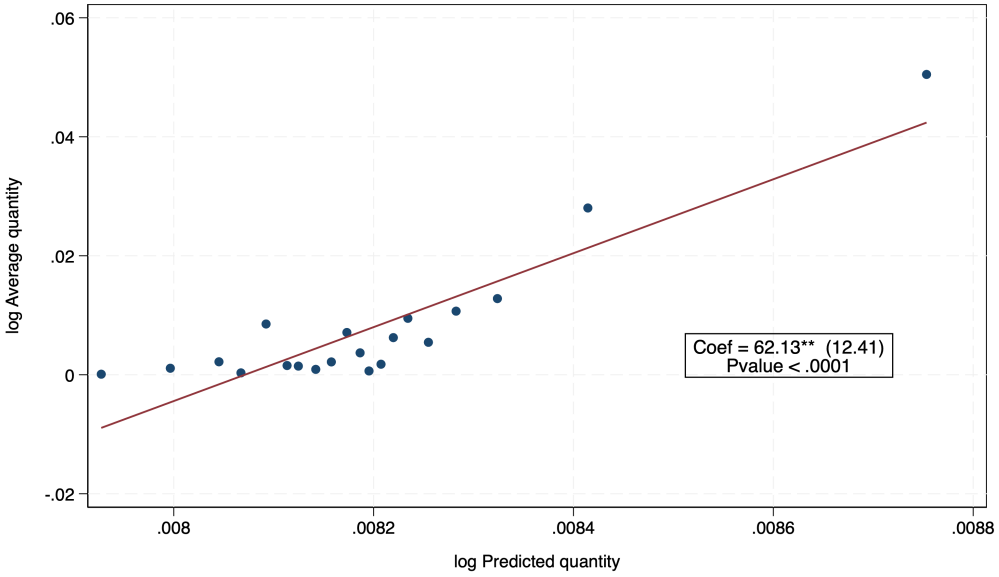
Notes: This figure presents the share of drug seized, in a given year and for a given drug, in the area for each period relative to the fight outbreak, separately for a general fight, and a fight involving at least one large gang. Moreover, it also shows the number of seizures for a general fight. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present.

Figure A40: Event study - seized quantity, means ← Return to text



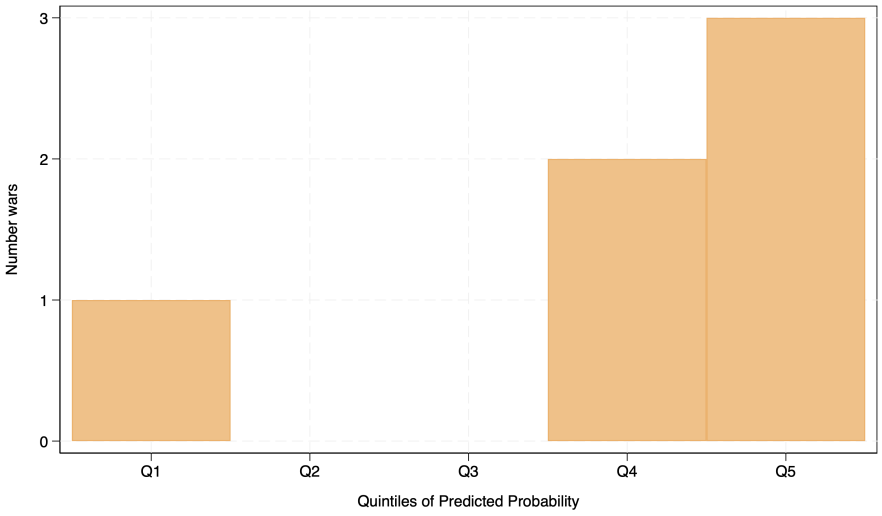
Notes: This figure presents scatter plot and linear fit of the log average share of drug seized in an area, in a given year, for a given drug, and the log average share predicted by the model.

Figure A41: Model fit - quantities ← Return to text



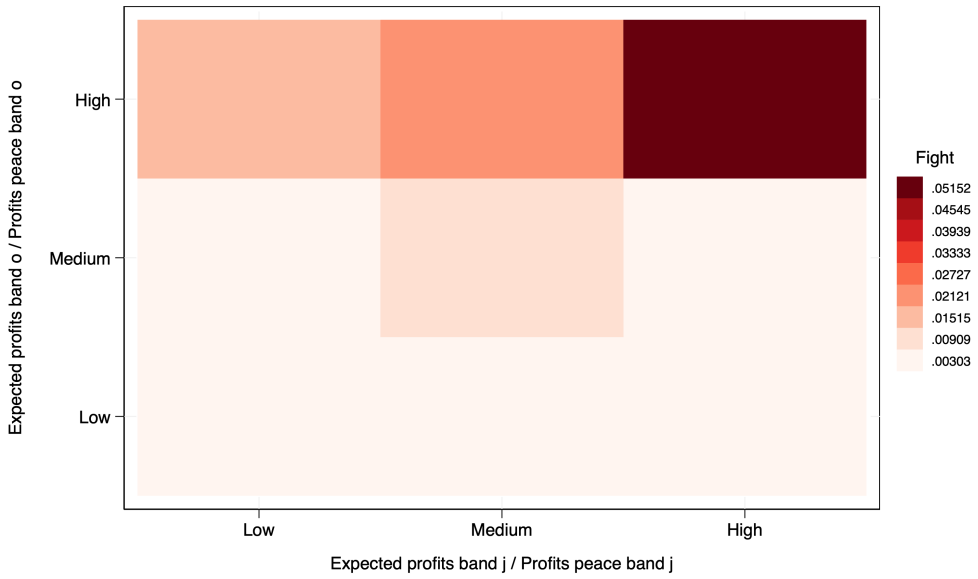
Notes: This figure presents scatter plot and linear fit of the log average share of drug seized in an area, in a given year, for a given drug, and the log average share predicted by the model. We exclude the city of Naples from the sample.

Figure A42: Model fit - quantities, no Naples ← Return to text



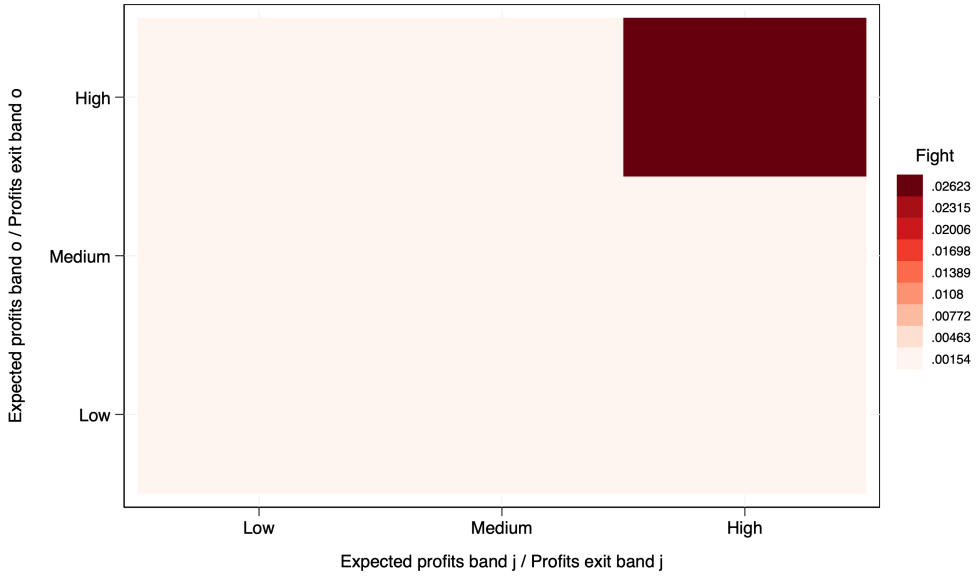
Notes: This figure presents number of fights in 2022 in the data for the 5 quintiles of the predicted fighting probability.

Figure A43: Correlation prob. fight and predicted probability ← Return to text



Notes: This figure presents the average observed fight probability in 2022 for the 3 tertiles of the ratio between expected profits and profits under peace of the dyad computed by the model.

Figure A44: Correlation prob. fight and profits (expected over peace) ← Return to text



Notes: This figure presents the average observed fight probability in 2022 for the 3 tertiles of the ratio between expected profits and profits under exit of the dyad computed by the model.

Figure A45: Correlation prob. fight and profits (expected over exit) ← Return to text

C Additional tables

Table A1: Summary statistics fights ← Return to text

# fights	100
# fights with known contended market	93
# fights with (known) winner	35
Mean number of gangs involved	3.25
Min number of gangs involved	2
Max number of gangs involved	14
# fights in areas with no gang present	0
# fights in areas with one gang present	13
# fights in areas with both gang present	80
Average number of periods in fight	1.49
Percentage fights lasting one period	72%

Notes: Table shows summary statistics of the fights in the data.

Table A2: Average scale and violence ← Return to text

Dep. Variable: Probability	(1) Homicide	(2) Homicide	(3) Gang Homicide	(4) Gang Homicide	(5) Fight	(6) Fight
Average scale	-0.0341**	-0.0315*	-0.0141	-0.0134	-0.0516***	-0.0412***
	(0.0171)	(0.0171)	(0.0252)	(0.0249)	(0.0122)	(0.0114)
Number gangs		0.0112		0.00313		0.0449***
		(0.0223)		(0.0207)		(0.0123)
Observations	753	753	503	753	753	503
R-squared	0.257	0.257	0.270	0.270	0.329	0.342
Area FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep | Average scale = 1	0.302	0.302	0.245	0.245	0.142	0.142
Dep. Variable: Number	Homicide	Homicide	1k p.c.	1k p.c. .	Gang 1k p.c.	Gang 1k p.c.
Average scale	-0.0837**	-0.0825**	-0.00438***	-0.00427**	-0.00247	-0.00218
	(0.0354)	(0.0407)	(0.00162)	(0.00170)	(0.00186)	(0.00179)
Number gangs		0.00529		0.000443		0.00127
		(0.0654)		(0.00244)		(0.00182)
Observations	753	753	503	753	753	503
R-squared	0.351	0.351	0.246	0.246	0.231	0.232
Area FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep | Average scale = 1	0.453	0.453	0.012	0.012	0.008	0.008

Notes: MWFE estimator. HDFE local linear regression. Average scale is the average scale of gangs in the area, measured as the number of areas in which the gang is present. Standard errors clustered at the location (district within Naples, city in the province) level. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. An homicide is coded as gang homicide if there was any gang mentioning on the internet related to the homicide.

Table A3: First stage - predicted entry ← Return to text

	Entry
IV	0.046***
	(0.002)
Observations	132,970
Area FE	Yes
Year FE	Yes
Gang FE	Yes
F-Stat	376.58

Notes: MWFE estimator. HDFE local linear regression. IV is the instrumental variable constructed as detailed in Section 3. Entry is a dummy variable indicating the entry of a gang in an area. A gang is defined to entry in an area at time t if is present in the area at t, but not in $t-1$. Location (district within Naples, city in the province), year, and gang fixed effects included int he model. Standard errors clustered at the location (district within Naples, city in the province) level. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively.

Table A4: Probability outcomes fights ← Return to text

	(1)	(2)	(3)
Fighting outcome	Win	Draw	Loose
Large	0.776*	-0.306	-0.0190
	(0.416)	(0.418)	(0.494)
Observations	70	70	70
Mean Dep | Large = 0	0.262	0.672	0.115

Notes: Dataset at the gang-year level. Sample composed by band-year observations with fights only. OLS linear regression. Large is a dummy variable indicating whether the gang is large or not. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. Outcomes are dummy variable indicating whether the gang has won, lost, or draw in the fight. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively.

Table A5: Data and model ← Return to text

Data	Model	Source
Network matrix	$\mathbf{Y}_t \ \forall t$	Inteligence data - Neapolitan Police
Matrix of fights	$\mathbf{F}_t \ \forall t$	Inteligence data - Neapolitan Police
# of arrests for drug dealing and related crimes	Measure $O_{ty} \ \forall y, t$	Administrative data - DCSA
Geolicalized seized drug type, quantity and time	Measure $q_{yvt} \ \forall y, t, v$	Administrative data - DCSA
Geolicalized quality of drug	$x_{vty} \ \forall y, t, v$	DCSA + Scientific Police
Average retail drug price over time and type	$p_{vt} \ \forall t, v$	Inteligence data - DCSA
Average wholesale drug price over time and type	$c_{vt} \ \forall t, v$	Inteligence data - DCSA
Distances between centroids of all markets	$g_{yy'} \ \forall y, y'$	Google maps API
Joint distribution of consumer groups and locations	$F(D_i, y_i)$	ISTAT + IPSAD survey

Table A6: Demand Estimation ← Return to text

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Step						
Outbreak fight (Lead 0 and Lead 1)	-0.00711	-0.0145**	-0.0145**		-0.00944*	-0.00944*
	(0.00603)	(0.00602)	(0.00602)		(0.00570)	(0.00570)
Retail price			-0.0000452	-0.0000452	-0.0000452	-0.000164
			(0.000328)	(0.000328)	(0.000328)	(0.00235)
Outbreak fight (Lead 0 and Lead 1) × Large				-0.0267*	-0.0169	-0.0169
				(0.0146)	(0.0155)	(0.0155)
Observations	1584	1149	1149	1149	1149	1149
R2	0.480	0.530	0.530	0.530	0.531	0.0125
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Drug FE	Yes	Yes	Yes	Yes	Yes	Yes
Selection	No	Yes	Yes	Yes	Yes	Yes
IV Price	No	No	No	No	No	Yes
KP-Stat						37.62
Mean Dep	0.012	0.012	0.012	0.012	0.012	0.012
Panel B: First Step						
(standardized) Arrests local police		0.593***	0.593***	0.593***	0.593***	0.593***
		(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Observations		1149	1149	1149	1149	1149
R2		0.461	0.461	0.461	0.461	0.461
Panel C: Distance						
Distance						-0.0009***
						(0.0002)
Observations						1545
R2						0.0179

Notes panel A: MWFE estimator. HDFE local linear regression. Dependent variable is the log of share of drug seized. Outbreak fight is a dummy variable equal to 1 in the lead 0 and lead 1 of the first fight in the area. Outbreak fight (Lead 0 and Lead 1) × Large is a dummy variable indicating the lead 0 and lead 1 of the first fight involving at least one large gang in the area. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Selection indicates the inclusion in the model of the control for selection, additional details in Section 5.
Notes panel B: OLS regression. Dependent variable is the number of drug seizures in the area, year, for a given drug. Independent variable is the number of arrests by the local police, standardized at the year-drug level. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively.
Notes panel C: OLS regression. Dependent variable is the city fixed effect estimated in panel A. Independent variable is the average distance from the considered city to all the others. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively.

Table A7: Police Rection Estimation ← Return to text

	(1)	(2)	(3)	(4)
Outbreak fight (Lead 0 and Leaf 1)	0.0301***			
	(0.0116)			
Outbreak fight (Lead 0 and Leaf 1) × Small		0.0321***		0.00278
		(0.0119)		(0.0130)
Outbreak fight (Lead 0 and Leaf 1) × Large			0.116***	0.113***
			(0.0201)	(0.0226)
Observations	533	533	533	533
R2	0.0125	0.0136	0.0583	0.0584
City FE	No	No	No	No
Year FE	No	No	No	No
Mean Dep lags	0.0055713	0.0055713	0.0035714	0.0035714
Outbreak fight (Lead 0 and Leaf 1)	0.00702			
	(0.00432)			
Outbreak fight (Lead 0 and Leaf 1) × Small		0.00737*		0.000854
		(0.00442)		(0.00501)
Outbreak fight (Lead 0 and Leaf 1) × Large			0.0251***	0.0244***
			(0.00788)	(0.00900)
Observations	533	533	533	533
R2	0.917	0.917	0.918	0.918
City FE	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Mean Dep lags	0.0055713	0.0055713	0.0035714	0.0035714

Notes: MWFE estimator. HDFE local linear regression. Dependent variable is number of arrests by the local police. Outbreak fight is a dummy variable equal to 1 in the lead 0 and lead 1 of the first fight in the area. Outbreak fight (Lead 0 and Lead 1) × Large is a dummy variable indicating the lead 0 and lead 1 of the first fight involving at least one large gang in the area. Outbreak fight (Lead 0 and Lead 1) × Small is a dummy variable indicating the lead 0 and lead 1 of the first fight involving only small gangs in the area. A gang is defined to be small if it has a scale of 3 or lower (90th scale distribution). The scale of a gang, in a given year, is the number of locations in which it is present. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively.

Table A8: Model fit - quantity ← Return to text

log Share drug seized	(1)	(2)	(3)	(4)
log Share drug simulated	0.731***	0.731***	0.732***	4.394***
	(0.0195)	(0.0195)	(0.0195)	(0.684)
Observations	1576	1576	1576	1576
R2	0.472	0.472	0.473	0.543
Drug FE	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
City FE	No	No	No	Yes

Notes: MWFE estimator. HDFE local linear regression. Dependent variable is log share of drug seized in a given city, year, and for a given drug. Independent variable is the log share simulated by the model. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively.

Table A9: Model fit - fights, correlations ← Return to text

	Fight	Fight 2022	Predicted prob.
Unobserved preference	0.257	0.200	0.300
Max scale	-0.069	-0.241	-0.062
Number gangs	0.346	0.213	0.880
Sd scale	-0.150	-0.316	-0.409

Notes: Table shows the correlations between fights incidence in the data, the same in 2022, and predicted fights probabilities, with the city fixed effects estimated in the demand equation, the maximum scale of gangs in the area, the number of gangs in the area, and the standard deviation of gangs scale in the area. Data at the location (district within Naples, city in the province)-year level. The scale of a gang, in a given year, is the number of locations in which it is present.

D Other data

Chemical analysis For a subsample of the previous dataset, we also have information on the chemical analysis of the seized drugs–the percentage of pure substance in the sample. When a penal litigation is opened after a seizure (which happens whenever the defendant does not plead guilty immediately), the judge should require chemical analysis from the forensic police as a preliminary step for the litigation. Indeed, Italian law requires a minimum percentage of pure substance to be present in the seized sample for the crime of drug dealing/trafficking to be established. Therefore, the forensic police performs the relevant chemical analysis, creates a folder with the results, and submits it to the judge. We construct two anonymized random samples of these analyses in three steps. First, we randomly draw 567 analyses from all the relevant folders (province of Naples, from 2015 to 2022 included). Each of these folders contains information on the identity of the defendant and the percentage of pure substance in the sample. Second, these analyses are merged internally with a private version of the drug seizures dataset containing information on the identity of the person receiving the seizures. To conclude, the resulting dataset is anonymized and shared with the research team. Given the high incidence of seizures in the city of Naples, 86% of chemical analyses in this first completely random sample are from the capital city. To increase the number of cities covered, in the second sample we stratify on the city-year-drug level, trying to draw few analyses from each stratum and, instead, to cover as many strata as possible. These efforts result in 660 chemical analyses, widely distributed across cities, years, and drugs. For each analysis in the two samples, we observe all the information from the seizure (city, year, quantity) and the percentage of pure drug. Therefore, we calculate, for each city, year, and drug, the within dispersion and average drug purity.

Average prices Each semester the Italian antidrug authority requires the three main enforcement authorities (*Polizia di Stato*, *Arma dei Carabinieri*, and *Guardia di Finanza*) to fill an official form with the average retail and wholesale prices, the average purity, and average quantity for each type of drug. We collect all these forms, and calculate the average retail and wholesale price for each year and type of drug.[13]

Homicides To measure violence, we use intelligence data on the list of homicides and attempted homicides in the province of Naples from 2015 to 2022. For each violent event, we have information on the victim, where the event happened, and when it happened. By using these

[13]The heroin wholesale price was missing for the period from 2019 to 2021. We impute it using the average between the two extreme available periods: 2018 and 2022.

information, we also identified whether the event was gang related or not by looking at online gang mentions associated with the event.

Arrests To measure police attention, we use the administrative data on the number of arrests. In particular, for each city and year in the sample, we observe the number of arrests for different drug related crimes and conspiracy (from the antidrug authority).

Mortality To measure overdoses, we use administrative data on mortality from ISTAT. For each city, in each year, we observe the number of deaths for each cause in a very granular list (ICD classification). In line with the guidelines of the ICD classification, we define a death to be overdose with codes: "X42", "X62", "F11", "F12", "F13", "F14", "F15", "F16", "F17", "F18", "F19", "P04", "P96", "R78", "T36", "T37", "T38", "T39", "T40", "T41", "T42", "T43", "T44", "T45", "T46", "T47", "T48", "T49", "T50", "Z79". We then compute the number of overdoses per each city and year.

Population To measure population size and demographics, we use administrative data on population from ISTAT. For each city and year, we observe the number of people living in the area by sex (Male or Female), age group (0-9, 9-24, 25-49, 50-64, >64), and educational attainment (no degree, primary school, lower secondary, upper secondary, bachelor, master or above). From these classifications, we create nine demographic groups using the intersections of three dummy variables: (i) male, (ii) young (age lower than 49), (iii) uneducated (lower than lower secondary educational attainment). We then compute the number of people for each demographic group, in each city. To project the number of people living in Naples across different districts within the city, we use the 2011 census of Naples city. For each district, we observe the percentage of people in the previously mentioned demographic groups. In particular, we directly observe from the census the percentage of people living in each district for the sex-education classification and age classification separately. We then estimate the percentage of people living in the district by multiplying these probabilities. This assumes no correlation between these two classifications, which is certainly an approximation. However, without an explicit relationship between the two, it is challenging to estimate the percentage in the intersection of the two. To conclude, we multiply this probability by the total number of people living in the city of Naples in each demographic group.

Distances To measure the distance between units, we used the Google maps API. In par-

ticular, we compute the average car travel time–independent from traffic conditions–between centroids of the different cities/districts, both in kilometers and seconds. We will use the distance in time.

Consumption survey To estimate the different propensity of drug consumption for different types of drugs and demographic groups, we use the publicly available aggregate statistics for the whole country from the IPSAD survey. This is an Italian survey following the guidelines provided by the EMCDDA (European Monitoring Centre for Drug and Drug Abuse) in Lisbon and allows the country to fulfill its information requirements regarding the first of the five epidemiological indicators proposed by the Council of Europe. The sample is drawn from the national population (through civil registry lists), aged between 15-84 years, and since 2005 has had a sample size (approximately 85,000 subjects) sufficient to allow prevalence estimates at the regional level. As public data, they provide average consumption propensity of different types of drugs across different demographic groups.

City survey To measure different characteristics of the cities in the sample, as well as the activity of the municipal police, we use a city survey from OpenCivitas. This is a portal for accessing local authorities' information, a transparency initiative promoted by the Ministry of Economy and Finance and SOSE. Each year–apart from 2020, due to Covid disruption–they send a survey to all cities in Italy. This survey collects balance sheet values, as well as different information on the services provided by the city. Importantly for this paper, they also collect information on the resources allocated to the municipal police as well as the outcomes of their activity (e.g., number of arrests).

E Additional Data and Empirics

E.1 Data quality assessment

This paper draws mainly on the intersection between two types of data: administrative and intelligence. Assuming that administrative data are complete and correct, this appendix assesses the quality of intelligence data by examining how administrative data vary with changes in intelligence data. Specifically, we examine whether and how raw administrative data (on violence, arrests, and seizures) respond to changes in intelligence data on presence and fights. If these responses align with expectations and are sufficiently precise, we can conclude that the intelligence data are of good quality.

As a first step, we examine how violence, arrests, and drug seizures change around fights. If fights are accurately measured, we should expect violence and enforcement activities to increase when fights break out, with no notable pre-fight increases and an overall reasonable pattern. Figure A46 shows the (standardized) number of homicides, gang homicides, drug arrests, arrests by local police, and drug seizures plotted against time relative to the first fight in each area. All outcomes remain close to their baseline levels before fights break out, with no evidence of shocks or substantial pre-trends. Exactly at the fight outbreak, we observe clear spikes in all outcomes. If there were substantial measurement error in fight timing, the pattern would be much less clear. This sharp trend around fight outbreaks therefore supports the quality of our intelligence data.

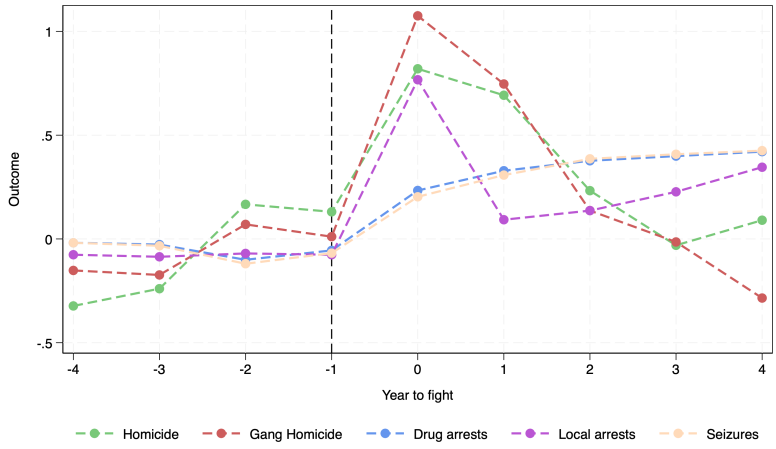


Figure A46: Data quality - variation with fights

Now we turn to the presence data. Given the increased probability of violence with a larger number of gangs (Figure A49), we can reasonably expect violence to increase when a new gang

enters an area. We can also think of this change as disrupting an existing equilibrium, thereby generating violence. We explore this intuition in Figure A47, where we plot the (standardized) number of homicides and gang homicides, and the probability of fights against time relative to the last entry in an area.[14] Exactly when a new gang enters an area, we observe an increase in the probability of fights (almost 100% increase), accompanied by an increase in violence in the following period, as expected.

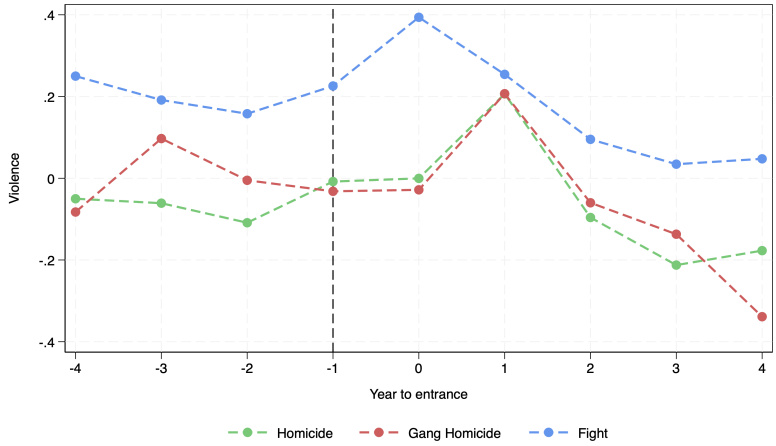


Figure A47: Data quality - variation with entry

To conclude, we examine the interaction between the two intelligence datasets. It is reasonable to expect that when a gang operates in multiple areas, violence increases with fights in all these areas, since this gang has potential targets in each location. Conversely, violence should not increase in areas where the fighting gang is not present, effectively serving as a placebo test. If we do not observe increased violence in these other areas, or if we observe increased violence in areas where neither fighting gang is present, this would raise doubts about the quality of our intelligence data. We explore this in Figure A48, where we plot the (standardized) number of gang homicides against time relative to the first fight. We examine three types of areas: the area where the fight occurs, other areas where one of the fighting gangs is present, and randomly selected areas where neither gang is present. At the outbreak of fights, we observe increased gang homicides in the first two area types, with comparable magnitude, though the increase is smaller in the other affected areas during the initial period, as expected. In contrast, we see no change in the placebo areas. If there were substantial measurement error in presence data (both in timing and actual

[14] We choose the last entry, rather than the first, to avoid confounding from successive entries, which could bias the results; a more detailed explanation is provided in Section 3.

recording), the patterns in these figures would be much less clear. The trend around fight outbreaks would not be so sharp, and either the spillover effect would be less pronounced (if presence is over-recorded) or there would be some effect in placebo areas (if presence is under-recorded).

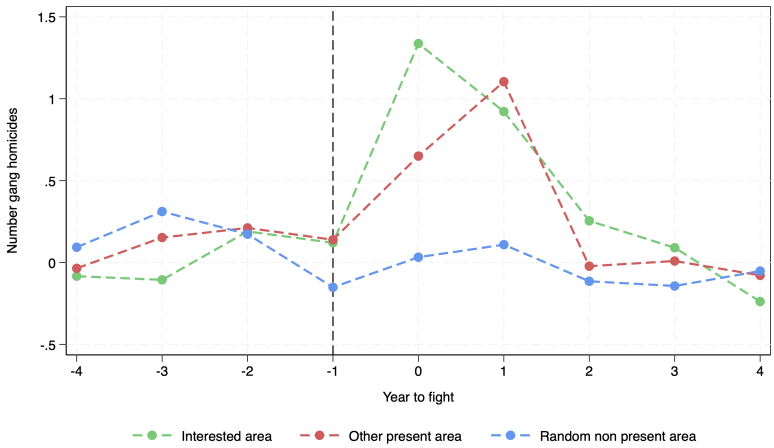


Figure A48: Data quality - variation with presence

Based on these exercises, we conclude that we observe reasonable and precise changes in administrative data corresponding to changes in intelligence data, which reassures us about their quality. Nevertheless, it should be clear that this does not constitute, nor is it intended to be, a formal test of data quality. Given the absence of alternative data sources, such validation is particularly difficult, if not impossible.

E.2 Additional descriptive evidence

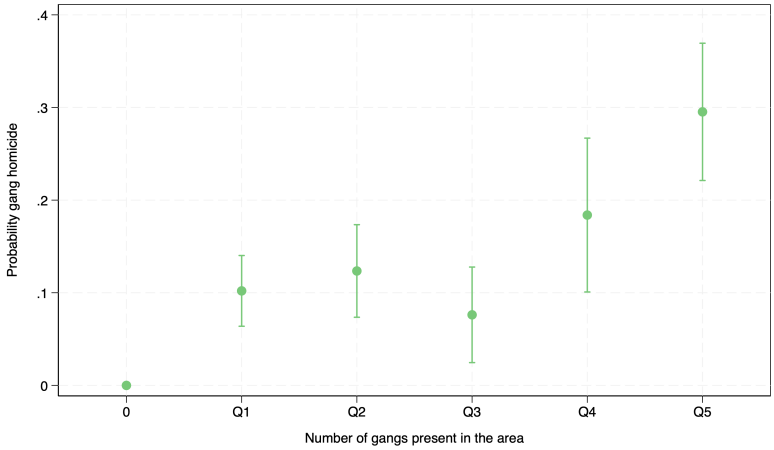
Figure A49 presents the average probability of gang homicide along with the 95% confidence interval for areas with no gangs (0) and separately for the five quintiles of the distribution of the number of gangs present in the area (0-20, 20-40, 40-60, 60-80, 80-100). As expected, the probability of gang homicide is exactly zero in areas with no active gangs. It increases significantly to approximately 10% in areas where a single gang holds a monopoly, and subsequently rises linearly with the number of active gangs, reaching a notable 30% in areas within the fifth quintile of active gangs. In summary, as the number of active gangs in an area increases, so does the probability of gang homicide. Figures A51 and A52 replicates for general homicide, rather than gang homicide, and fights in the area respectively.

Figure A50 illustrates how the probability of gang homicides varies with the standard deviation of the active gangs' scale. We observe an inverse U-shaped relationship between these two dimensions. In areas where the active gangs are very similar in size (whether small or large), the probability of gang homicide is relatively low. As the differences in gang sizes increase, so does the level of violence in the area. Around 1 standard deviations of gang scale, the probability of gang homicide reaches its peak before quickly declining. At the other extreme, where there is a significant inequality in the distribution of active gangs, the probability of gang homicide falls to its lowest point. Thus, violence is reduced when power in an area is balanced–making conflict outcomes too unpredictable–and when it is extremely unbalanced–making conflict outcomes too predictable. Figures A53 and A54 replicates for general homicide, rather than gang homicide, and fights in the area respectively.

Figure A55 illustrates the number of active gangs across the province over time (shown in blue), along with the average number of gangs per area (shown in red). Over the sample period, the total number of active gangs in the province has increased significantly, from approximately 75 in 2015 to 85 in 2022. Notably, there was a sharp rise in the number of gangs following the Covid outbreak, continuing until the end of the restrictions from 2019 to 2021. The average number of gangs per area is consistently higher than one in each period, indicating the presence of multiple gangs in each area. As the number of gangs increases, so does the average number of gangs per area.

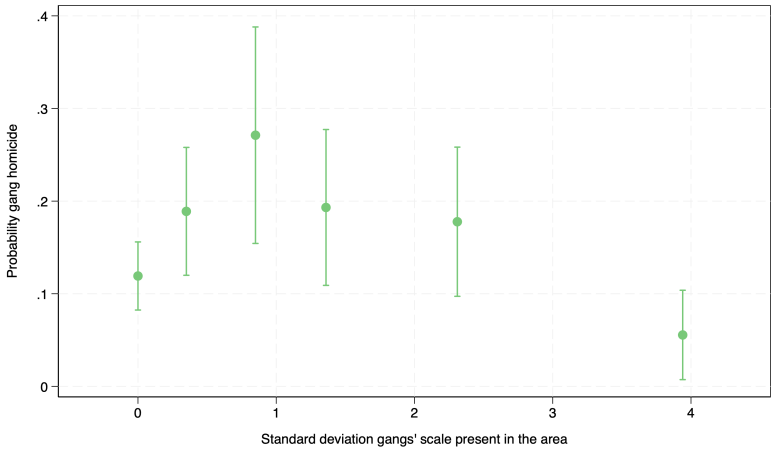
Figure A56 illustrates the time trend of violence. The number of homicides remains fairly stable over time, potentially showing a slight decrease over the sample period. In contrast, attempted homicides exhibit a noticeable spike during the Covid-19 period.

To gain a better understanding of the temporal variation in the data, Figure A57 presents the transition matrix illustrating the changes in the number of gangs present in the areas over time.



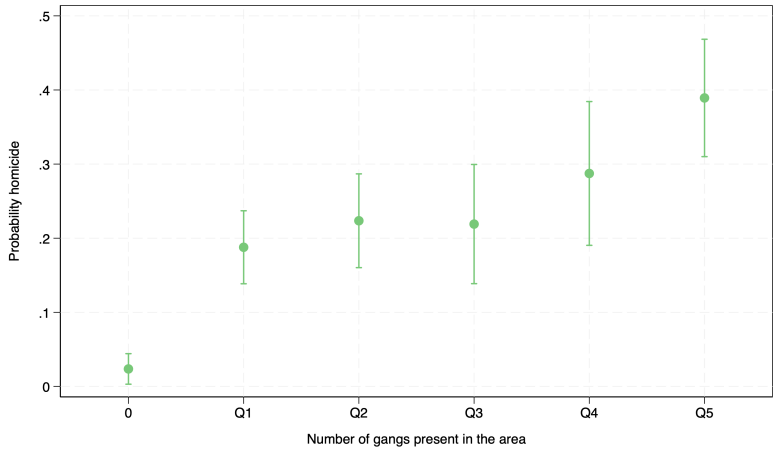
Notes: This figure presents the average probability of gang homicides for locations-years with no gangs, and for the five quintiles of the number of gangs present in the area distribution. An homicide is coded as gang homicide if there was any gang mentioning on the internet related to the homicide.

Figure A49: Prob. gang homicide by number of gangs



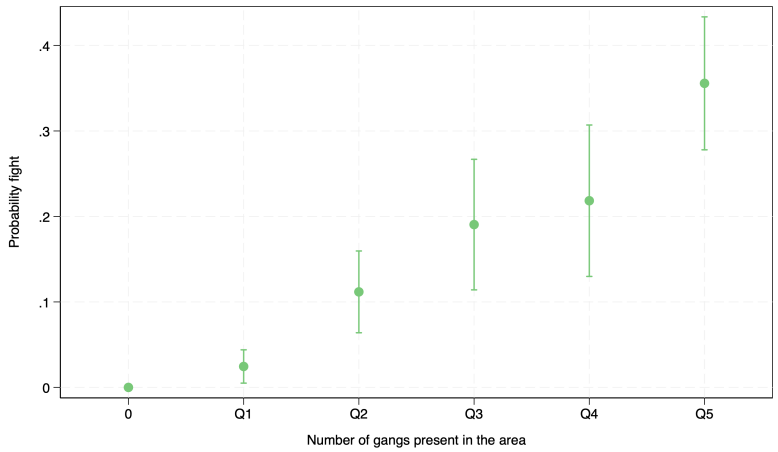
Notes: This figure presents the average probability of gang homicides for locations-years with no gangs, and for the five quintiles of the standard deviation of scale of gangs present in the area distribution. An homicide is coded as gang homicide if there was any gang mentioning on the internet related to the homicide. The scale of a gang, in a given year, is the number of locations in which it is present.

Figure A50: Prob. gang homicide by sd scale



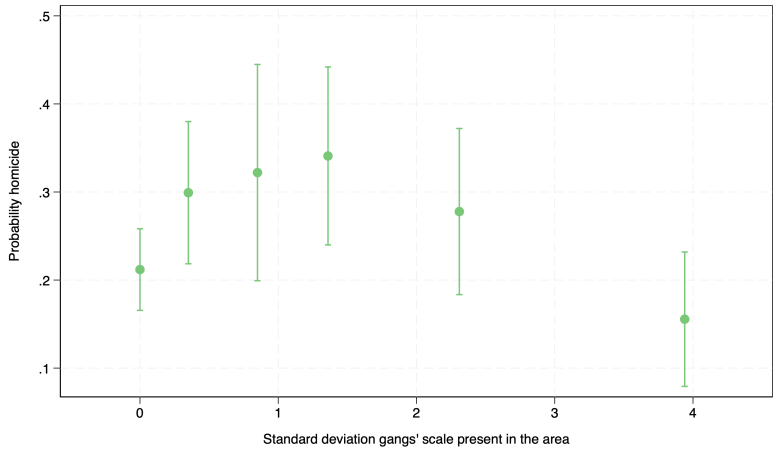
Notes: This figure presents the average probability of homicides for locations-years with no gangs, and for the five quintiles of the number of gangs present in the area distribution.

Figure A51: Prob. homicide by number of gangs



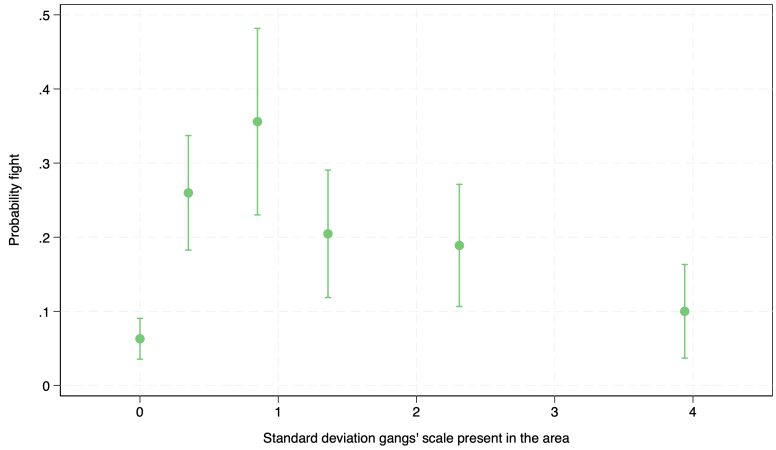
Notes: This figure presents the average probability of fights for locations-years with no gangs, and for the five quintiles of the number of gangs present in the area distribution.

Figure A52: Prob. fight by number of gangs



Notes: This figure presents the average probability of homicides for locations-years with no gangs, and for the five quintiles of the standard deviation of scale of gangs present in the area distribution. The scale of a gang, in a given year, is the number of locations in which it is present.

Figure A53: Prob. homicide by sd scale ← Return to text



Notes: This figure presents the average probability of fight for locations-years with no gangs, and for the five quintiles of the standard deviation of scale of gangs present in the area distribution. The scale of a gang, in a given year, is the number of locations in which it is present.

Figure A54: Prob. fight by sd scale ← Return to text

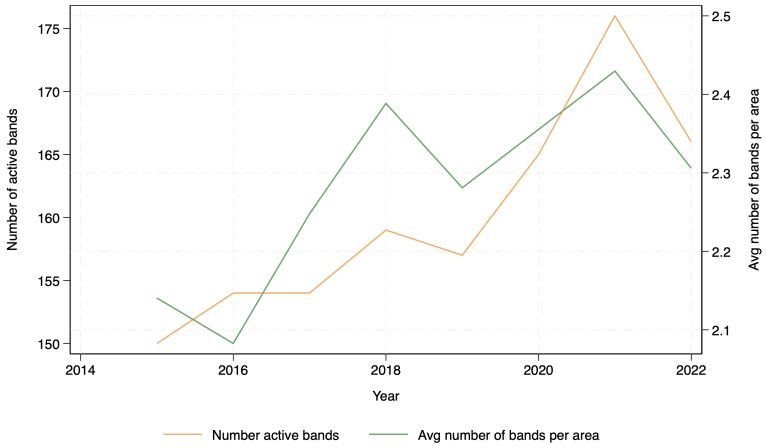


Figure A55: Number of active gangs

Two equilibriums appear to be relatively stable: areas with no gangs and areas with a very large number of gangs (more than 5 present simultaneously). In contrast, intermediate equilibriums seem to be quite unstable. For instance, the data indicate a 24% probability of transitioning from 3 gangs today to 2 gangs tomorrow.

Table A10 provides summary statistics on average quality and average prices for each drug type. Figure A58 illustrates the distribution of observed drug quality–measured as the percentage of pure substance–for the three types of drugs considered in this paper. There is significant heterogeneity across drugs, with an average purity of 62% for cocaine, 22% for heroin, and 14% for marijuana. Moreover, there is substantial variation within each category of drug. For instance, we observe doses of cocaine ranging from 2% to 98% pure substance, indicating that we have data covering the entire spectrum of drug quality.

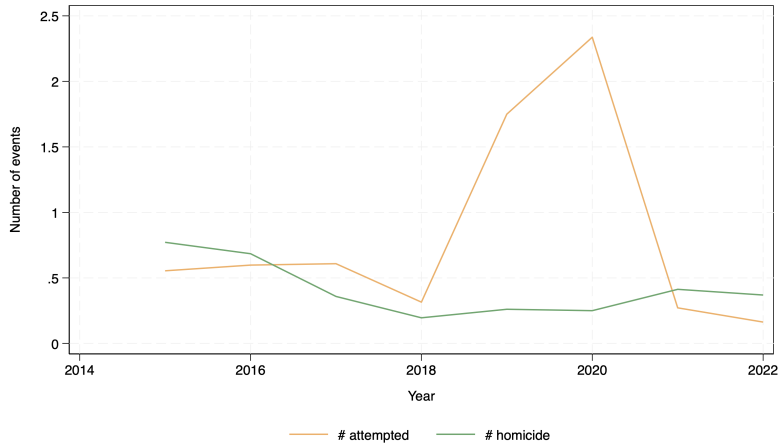


Figure A56: Time trend violence

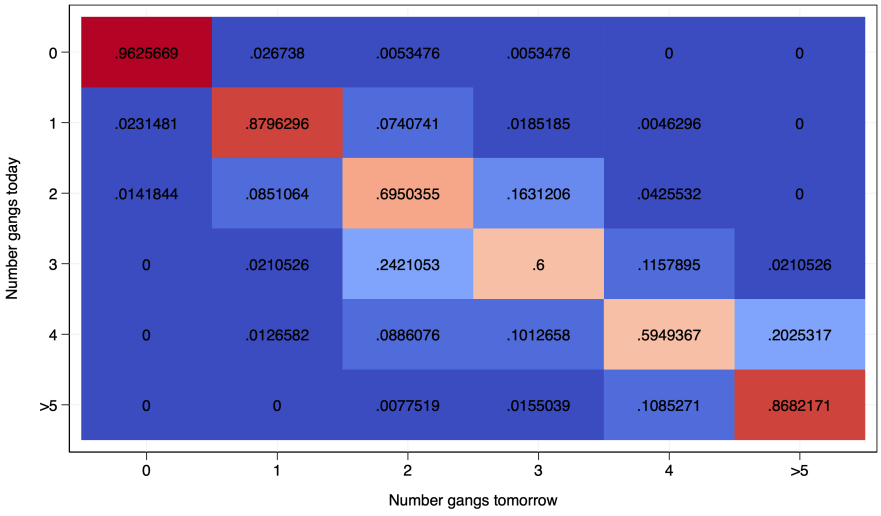


Figure A57: Transition matrix - number of gangs in the area

Table A10: Summary statistics drugs

	Mean	SD	Min	Max
Quality cocaine	61.76	20.21	2	98
Average retail price cocaine	77.81	11.21	67.5	95
Average wholesale price cocaine	38.25	2.60	35	42
Quality heroin	21.19	12.3	0.63	76.5
Average retail price heroin	63.75	10.61	45	75
Average wholesale price heroin	25.19	5.66	15	32
Quality marijuana	13.78	6.96	0.2	58
Average retail price marijuana	11.19	2.23	9	15
Average wholesale price marijuana	2.58	0.57	2	3

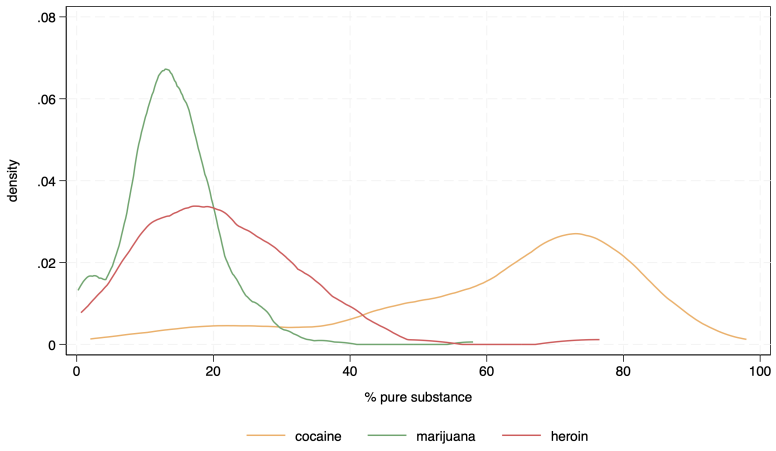


Figure A58: Distribution drug quality