Murder in the Marketplace

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Abstract

Violence is often viewed as an intrinsic feature of illicit markets, driven by competition, disputes, and predation. We argue that the connection between violence and markets is not exclusive to illicit markets and that in the absence of strong institutions these factors exist ubiquitously. Using an estimator of spatial concentration, we document the empirical relationship between violence and markets in the 14^{th} century. We then employ a large language model to analyze the coroner's accounts of the era's homicides, finding that many of these incidents were driven by avoidable escalations of business-related disputes. Employing a novel difference-in-differences estimator for spatial concentration, we proceed to causally identify the impacts of the introduction of London's first professional police force in the 19^{th} century on this concentration. We find that the police force's introduction led to a 54% reduction in the degree of concentration of violence around marketplaces. Our findings suggest that it is not the nature of the commodities being sold in illicit markets that drives violence, but is rather the absence of formal institutions of enforcement and dispute resolution.

Keywords: marketplace violence, medieval violence; spatial concentration; local large language model
JEL Codes: K42; N93; R12; C21; K40; N90
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1 Introduction

Violence is a well documented intrinsic feature of illicit markets. Within the markets for illegal narcotics, the systemic violence model of Goldstein (1985) holds that violence arises from predation, disputes, and competition among both sellers and users. Competition over resources in the absence of formal oversight pushes the markets for illegal goods towards violent conflict. In states of anarchy, individuals are left susceptible to predation by those stronger than them seeking control over scarce resources (Skaperdas, 1992). The same is true in illicit markets where, in the absence of formal property rights, participants are left vulnerable to robbery and victimization (Jacques, Rosenfeld, Wright and van Gemert, 2016). The lack of formal enforcement mechanisms that support property rights or arbitrate disputes within criminal markets allows for violence to become a dominant strategy (Donohue and Levitt, 1998). Here, we turn our attention in a novel direction, asking empirically whether the same intrinsic relationship between violence and illicit markets existed in the markets for legal commodities when formal enforcement mechanisms were similarly absent.

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To explore this question, we examine two historical settings divided by centuries, and document a persistent relationship between violence and marketplaces. First, we develop a simple conceptual framework to concretize this relationship between violence and markets, and to generate testable predictions regarding the roles played by enforcement and arbitration in that relationship. We then empirically examine the spatial concentration of murders around street markets in 14^{th} century London, a period long before the development of a formal police force. Indeed, throughout history, it has not solely been the markets for illicit narcotics that were absent formal enforcement and dispute resolution mechanisms. Until relatively recently in history, formal professional police forces did not exist. In the period before professional policing became the norm, communities were guarded sporadically by neighborhood level night watchmen (Rawlings, 2008) and routine day to day disputes were generally handled informally (Barron, 2004a). Issues arising between working class individuals often were solved through semi-organized brawls (Newell, 2016). Businessmen, on the other hand, often embedded themselves within formal guilds which negotiated and arbitrated disputes on their behalf (Ogilvie, 2014). However, in their handling of disputes, conflict between guilds often arose to physical violence (Hanawalt and Hanawalt, 2017, p. 37). Finding a strong and statistically significant relationship between the spatial distributions of marketplaces and violence, we proceed to examine the coroner's accounts of those 14^{th} century homicides and employ a locally hosted large language model to provide insights into the motives for these murders and the mechanisms linking violence to marketplaces in the era.

Second, we jump ahead in time to the 19^{th} century to provide plausibly causal evidence of the role that enforcement and arbitration play in sustaining that spatial dependency. To do so, we derive a novel difference-in-differences estimator for spatial concentration and exploit the jurisdictional peculiarities of London's first professional police force. We find a substantial reduction in the degree of concentration of homicides in the vicinity of marketplaces within the jurisdiction of the London Metropolitan Police following their 1829 formation, relative to the marketplaces outside of their purview.

The high prevalence of violence in illicit markets is extremely well documented. Reuter (2009) provides an overview of the systemic theory of violence, exploring why illegal drug markets in particular see such high rates of murder. Recent work including Sobrino (2020), Castillo, Mejía and Restrepo (2020), Daniele, Le Moglie and Masera (2023), Porreca (2023), and Park (2025) have empirically examined competitive dynamics linking illegal drug markets to violence. Goldstein (1985)'s systemic theory of violence holds that violence in these markets is often the result of robberies, disputes, and contract or norm enforcement. As a driver of drug violence, robbery is not unique to the illicit market setting. Robbery and other crimes are quite susceptible to deterrence effects and can be reduced by changes in policing practice (Becker, 1968; Chalfin and McCrary, 2017; Maheshri and Mastrobuoni, 2021). Disputes and contract or norm enforcement, the other primary categories of the drivers of drug violence from Goldstein (1985)'s systemic theory, exist across society, yet in other settings fail to spur the same violent outcomes. Jacobs and Wright (2008) argue that even much of the robbery within the illicit markets is a form of dispute resolution. This raises the question of why disputes and contract/norm enforcement breed violence in some markets but not others.

We argue that the reason is that in legitimate markets the state provides a formal backdrop for dispute resolution and contract enforcement. While the state is available to arbitrate disputes through the legal system for legal markets, its absence forces violence to serve as a means of redress in illicit markets (Rasmussen, 1994, p. 101-102). The same conditions that today cluster violence around the markets for illegal drugs have historically existed in all markets. Where disputes arise, there is the possibility for violence to emerge in the absence of sufficient arbitration opportunities. We find that in the medieval setting, homicides are 153% more concentrated around marketplaces than would be expected under a random spatial distribution of violence. Our analysis with a local large language model demonstrates that the bulk of these murders were precipitated by factors directly related to business and most could have been avoided had alternative means of dispute resolution been available. In more contemporary 19$^{\text{th}}$ century Georgian London, we find that marketplaces in areas under the newly formed London Metropolitan Police's jurisdiction saw murders grow 54% less concentrated in their vicinity following the Met's debut when compared to marketplaces outside their jurisdiction. The weight of our evidence suggests that what drives violence in illicit markets is not unique or a characteristic of the illegal commodities sold. Rather, just like in these illegal markets it is the absence of formal dispute resolution or contract enforcement mechanisms that allows violence to arise from economic activity. What we see today in unregulated illegal drug markets is much the same as what was seen in all markets before the formalization of institutions that normalized business behavior.

In the remainder of the paper we proceed as follows: Section 2 provides a simple model to serve as a conceptual framework demonstrating the pathways linking violence and market activity. Sections 3 and 4 present and discuss our findings from 14$^{\text{th}}$ century and 19$^{\text{th}}$ century London, respectively, while Section 5 concludes.

2 Conceptual Framework

Here, we present a simple conceptual framework that illustrates the connection between violence and markets. Within this framework, we nest the predictions of our empirical models. The model is not meant to be all-encompassing or to completely mirror reality. It is solely meant to illustrate the logic behind the relationship between markets and violence and to lay the foundation for our later identification strategy.

We posit that violence arises from two primary channels: crime (which can escalate to violence) and disputes (which also can escalate to violence). Further, there is a stochastic element to the occurrence of violence. Routine crime at the local level is modeled with a Beckerian framework:

$$C_{it} = f(\Pi_{it}, \Theta_{it}, \epsilon^c_{it})$$

Local crime is a function of a deterrence component (city wide penalties and local enforcement effort), Θ_{it}, the benefits to crime locally, Π_{it}, and a stochastic component specific to local crime, ϵ^c_{it} . In line with the framework of Becker (1968), both the benefits of crime and the deterrence components are functions of the expected probability of facing enforcement for a particular crime's commission.

$\Pi_{it} = (1 - p_i)(\pi_{it})$, where π_{it} is average benefit to committing a crime in the area, and p_i is probability of facing enforcement effort for a crime committed in that area.

and

$\Theta_{it} = (p_i)(\theta_{it})$, where θ_{it} is the average penalty for crimes committed in that area.

Local rates of dispute are area specific with a stochastic component. The area specific dispute component, which is fixed and time invariant, is meant to encapsulate all unmeasured (or not explicitly accounted for in the model) features of locations that may lead to higher dispute rates (and in turn higher rates of violence). The local dispute rate is represented as:

$$D_{it} = (\mu_i + \epsilon_{it}^D)$$

Parameters v^D and v^C are common parameters that represent the rates by which disputes and routine crime escalate to violence, respectively. Thus the overall level of violence in a location can be represented as the sum of violence arising from disputes, routine crime, time-invariant location peculiarities, and the stochastic component.

$$V_{it} = v^D(D_{it}) + v^C(C_{it}) + \epsilon_{it}^V$$

$$V_{it} = v^D(\mu_i + \epsilon_{it}^D) + v^C(f(\Pi_{it}, \Theta_{it}, \epsilon_{it}^c)) + \epsilon_{it}^V$$

$$V_{it} = v^D(\mu_i + \epsilon_{it}^D) + v^C(f((1 - p_i)(\pi_{it}), (p_i)(\theta_{it}), \epsilon_{it}^c)) + \epsilon_{it}^V$$

Both escalation parameters, v^j, are functions of locally specific time varying stochastic elements, allowing for randomness in the rate at which violence arises from routine crime and other disputes. They are also impacted by deterrence factors, being functions of p_i. However, v^D, the rate at which disputes escalate to violence, is also a function of the presence of arbitration opportunity, α.

$$v^D = f(p_i, \alpha, \epsilon_{it}^v); \frac{\partial v_i^D}{\partial \alpha} < 0; \frac{\partial v_i^D}{\partial p_i} < 0$$

and

$$v^C = f(p_i, \epsilon_{it}^v); \frac{\partial v_i^C}{\partial p_i} < 0$$

We will utilize this basic framework in this paper's subsequent sections to motivate the predictions that we will test empirically.

3 Violence and Marketplaces

Violence in general is a function of numerous components, as enumerated above. However, more interestingly, our conceptual framework allows us to look particularly at the spatial dimensions of violence. With the basic set up from our conceptual framework in mind we can illustrate the logic linking markets and violence. For simplicity, we will assume that there are only two types of locations, markets and non-markets, replacing i in the above formulation with M and $-M$.

We introduce two assumptions here. First, that the profit to be made from routine crime is on average greater in marketplaces than in non-markets: $\pi_M > \pi_{-M}$. Second, that disputes are more likely to arise in areas in which business is conducted, i.e. markets, than in non-markets: $\mu_M > \mu_{-M}$. The first of these assumptions is simple enough to digest, being consistent with the rational choice model of crime of Becker (1968), as well as criminological theories including rational choice theory (Cornish and Clarke, 2014) and routine activities theory (Cohen and Felson, 2010). The second assumption is similarly grounded in rational choice theory.

Following from the set up from this framework, we can by definition observe that for any given time period, $\mathbb{E}[V_M] > \mathbb{E}[V_{-M}]$. Now, we will proceed to demonstrate this empirically, in the context of medieval London. Following a bit of historical background, we demonstrate that incidents of 14$^{\text{th}}$ century violence within the city were disproportionately clustered around the era's urban marketplaces, providing some empirical evidence supporting the prediction of our modeling framework.

3.1 Historical Background

Marketplaces played a central role in Medieval London as hubs for people to trade and bargain. However, the bustling trade also created an environment ripe for conflict. According to Barron (2004c), by the beginning of the 13$^{\text{th}}$ century, merchants and craftsmen trading similar goods started to settle within specific areas of London, populating particular marketplaces. This agglomeration process, however, did not always take place in peace (Barron, 2004c, p. 229). Merchants often had to fight to secure their space within their specific market. Then, once settled, merchants had to continually defend their positions from competition within the market. Trade-related incidents, in addition to the power struggles between merchants, were a further major source of conflict. Controversies over sales and purchases, debt collections, and working contracts were debated on a daily basis, and frequently arose to violence (Hanawalt, 1998, p. 39).

The externalities of violence endangered the quality of life of everyday Londoners. In the hopes of remedying the high levels of violence across England, in the 13$^{\text{th}}$ century, Edward I extended the duties of village watchmen to encompass a role reminiscent of the investigatory and enforcement functions of police (Summerson, 1979, p. 325). However, watchmen were meant to patrol throughout the night, leaving day time activity relatively unprotected (Bindler and Hjalmarsson, 2021, p. 3067). In the absence of a formal police force, informal means of conflict resolution were frequently employed throughout the era. While the courts were generally effective in solving complicated commercial disputes (Barron, 2004b, p. 61), informal arbitration and mediation were also largely employed as alternatives (Hanawalt, 1998, p. 36). City officials acted as mediators between powerful guilds or craftsmen groups in order to avoid having the dispute advance to the courts or devolve into violence or riots (Hanawalt, 1998, p. 43). However, given the absence of a regular formal institution able to resolve day to day conflicts, or to deter routine criminal activity with a credible threat of punishment, violence became a common feature of life in medieval England.[1]

3.2 Data

We collected 14$^{\text{th}}$ century homicide data from the University of Cambridge's Medieval Murder Map website.[2] These digitized records, derived from London Coroners' Rolls, document the findings of investigative juries summoned after sudden, suspicious, and violent deaths in 14$^{\text{th}}$ London (Eisner, 2023). The records contain information reported by the coroner about incidents which caused sudden and violent death, including accidents, injuries, and murders. Each case includes the date, the location, and the weapons used. More notably, each incident is accompanied by a brief summary describing what happened and identifying the parties involved. As we explain in Section 3.4, these information were crucial to identify which homicides were linked to market disputes and economic activities; Additionally, the *Medieval Murder Map* overlays these incidents onto a reconstructed map detailing London between 1270 and 1300[3], which highlight the key landmarks of the period such as churches and prisons. In total, we retrieved 144 geolocated homicides between 1300 and 1342.[4] Over this period, at least one homicide was recorded in 18 of the 42 years, with the majority of homicides occurring in 1339 ($n = 23$).

Information on medieval marketplaces come from *The Agas Map of the Early Modern London* website (MoEML Team, 1999). The MoEML is an ongoing digital project that provides an annotated, interactive version of the map, linked to an encyclopedia detailing historical landmarks, including marketplaces. Using information from the MoEML encyclopedia, we were able to identify and map the ten major marketplaces that existed in the early modern City of London.[5]

To summarize, Figure 1 shows the locations of London's medieval marketplaces throughout the city.

[1] To this point, it is recorded that some 330 homicides occurred in the county of Gloucestershire in the single year 1221 (Summerson, 1979, p. 324).

[2] The interactive map was created by Eisner (2023); first accessed December 2024, last accessed January 2025.

[3] The basemap of medieval London was revised by Barron (2019) starting from a version of the map of the 1270 London map which was published in the Atlas of London up to 1520.

[4] The website lists 142 geolocated murders out of 149 total Via API we were able to extract 144 geolocated homicides.

[5] Of these ten markets, eight were already clearly prominent between the 9$^{\text{th}}$ and the 13$^{\text{th}}$ centuries while two had already been established but would be further developed by the 15$^{\text{th}}$ century (MoEML Team, 1999).

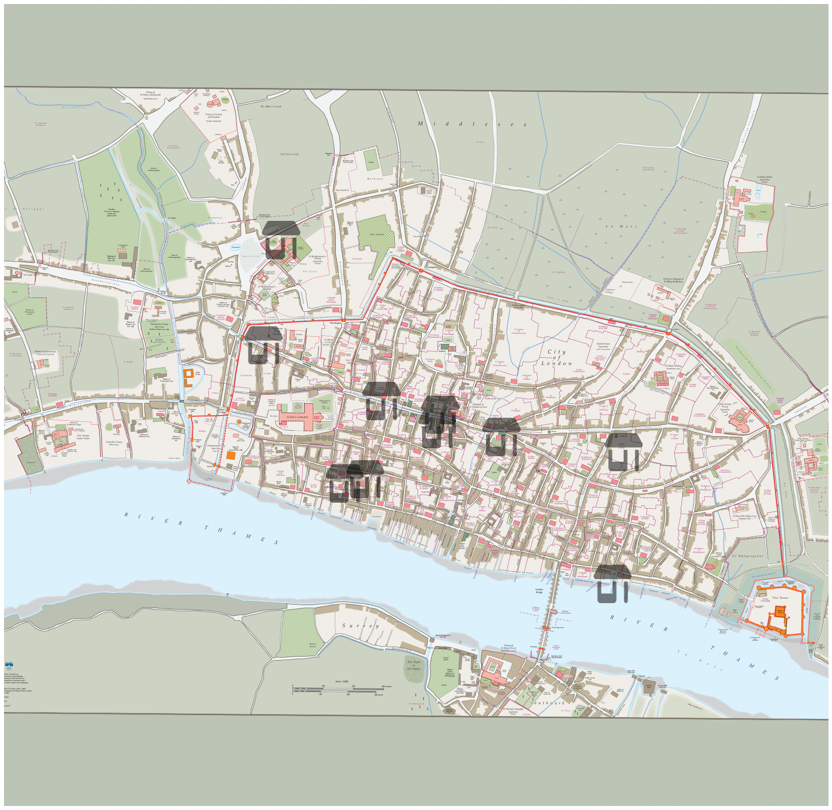


Figure 1: Figure depicting the locations of London's medieval marketplaces.

3.3 Empirical Strategy and Results

Given that there are not clear cut boundaries for what constitutes a marketplace and what does not, it is most accurate to treat space as a continuous plane, labeling markets as points representing their centroids. Within this framework we are able to quantify the concentration of violence within the immediate vicinity of markets. To do this, we employ the cross-type K function. This function plots a curve depicting the expected number of observations of type j to be found in increasing radii surrounding random type i observations, scaled by the intensity of the type j point process (Dixon, 2013). Dixon (2013) provides the following representation of the *true* K function:

$$K_{ij}(r) = \frac{1}{\lambda_j}\mathbb{E}(observations\ of\ j\ within\ a\,distance\ of\ radius\ r\ of\ a\ random\ i\ observation) \quad (1)$$

λ_j represents the intensity of the type j point process (the total number of type j observations divided by the entire area of the studio window- the average number of observations per unit of space). Within our context, evaluating the spatial relationship between homicides in the medieval era and the locations of marketplaces, we treat the centroids of marketplaces as our type i observations and allow the locations of homicides to be our type j observations. Thus the K function shows us the expected number of homicides found within radius r of a random marketplace. A common estimator (the so-called Ripley's K) of this function is provided in Lotwick and Silverman (1982) and (Dixon, 2013):

$$\hat{K}_{ij}(r) = \frac{1}{\lambda_i \lambda_j A} \sum_k \sum_l \mathbb{1}(d_{i_k,j_l} < r) \tag{2}$$

In that equation, λ_i represents the intensity of the marketplace spatial point process and A is the area of the study's window. d_{i_k,j_l} represents the distance between kth observation of type i and the lth observation of type j. Thus, inside the double summation is an indicator function for whether a point of type j is found at any given radius of a type i point. The double summation provides a count of points found below any given radius.

Here, we can directly map this measure of concentration to our conceptual framework with the introduction of a single tractable assumption. We assume that $\frac{\partial pr(\mathbb{1}(d_{i_k,j_l}<r)=1)}{\partial V_i} > 0$. This assumption simply holds that if overall levels of violence increase in type i areas, then the probability of observing an instance of violence in the area surrounding a type i observation also increases. Thus, the summation at the core of our K function estimator will increase as levels of violence increase.

Moving forward, for the purpose of generating test statistics from this curve, we will refer to that estimated cross-type K function from our observed intensity and spatial point process as $\hat{K}_{obs}(r)$. To generate statistics to be used for hypothesis testing, we will compare that observed cross-type K function to what would be observed under complete spatial randomness, what we will term $\hat{K}_{pois}(r)$. This represents the estimated K cross function that would arise if the locations of type j observations were drawn from a homogeneous Poisson process, rather than the true spatial point process, with the same intensity as that observed.

We compare the estimated cross K function, $\hat{K}_{obs}(r)$, to the curve of a homogeneous Poisson generated point process, $\hat{K}_{pois}(r)$. The potential gap between these two curves tells us whether the spatial point processes governing the locations of type j and type i observations are more or less closely linked to one another than random. If the observed curve were to be above the homogeneous Poisson curve, this would indicate that type j observations are more clustered around type i locations than would be expected under a null hypothesis of a random spatial distribution of j's. Here, this would indicate that murders are more concentrated around marketplaces than a random point process covering the same study window would be able to generate. Keeping this within the language and predictions of our conceptual framework, we can state that if $V_M > V_{-M}$ then $pr(\mathbb{1}(d_{M_k,j_l} < r) = 1) > pr(\mathbb{1}(d_{-M_k,j_l} < r) = 1)$. The probability of observing a murder in a given distance from a marketplace is greater than the probability of observing a murder at the same distance from a random non-marketplace point. By comparing the observed curve to the Poisson curve, we are testing against the alternative that $pr(\mathbb{1}(d_{M_k,j_l} < r) = 1) = pr(\mathbb{1}(d_{-M_k,j_l} < r) = 1)$. To formally test this difference in spatial concentration empirically, we calculate the following mean deviation test statistic:

$$\theta = \frac{1}{R} \int_0^R (\hat{K}_{obs}(r) - \hat{K}_{pois}(r))dr \tag{3}$$

With R representing the maximum radius considered, this provides the average distance between the curves. Positive values indicate more clustering than random and negative values indicate less clustering than random. We calculate σ_θ^2, the variance of our mean deviation statistic, using the spatial bootstrap estimator of Loh (2008) with 5000 repetitions.

Looking towards medieval murders, $\theta = 0.199$ with an associated p-value of 0.04 (a t statistic equal to 2.11). Thus, there is a substantial concentration of homicides around marketplaces in medieval London. Homicides were over 150% more concentrated around marketplaces then would be expected under spatial randomness.[6] Below we present this graphically, showing the observed K curve (in black) riding consistently above the range of curves generated from homogeneous Poisson point processes.

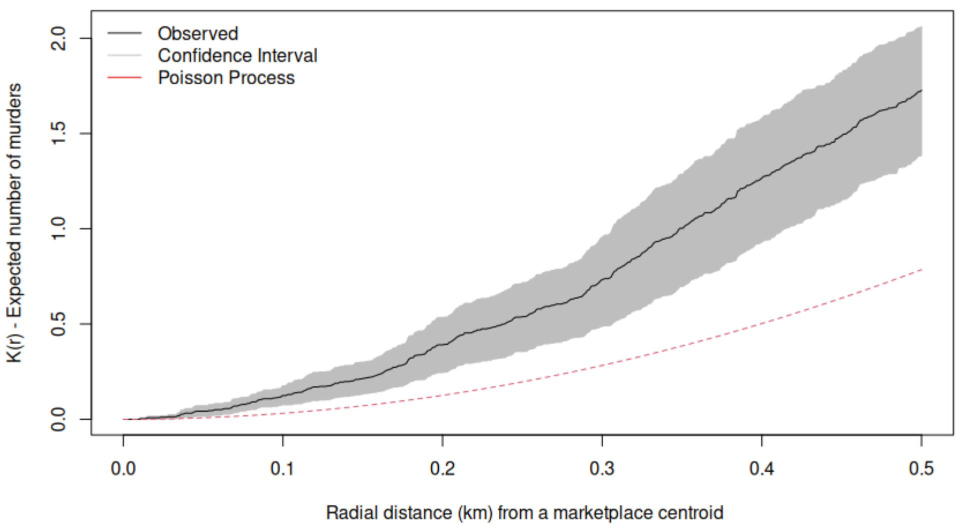


Figure 2: Figure depicting the observed cross-type K curve, with its 95% confidence interval, and the curve generated under a homogeneous Poisson process.

We replicate this exercise using deaths stemming from accidents and illnesses as a placebo. This still yields a positive spatial concentration ($\theta_{placebo} = 0.0.96$ with a t statistic of 1.28). While it is not particularly surprising that deaths stemming from illnesses and accidents also concentrate to a degree around hubs of economic activity (albeit without enough concentration to garner statistical significance), it is perhaps more informative to compare this degree of concentration to that observed for violence. We proceed to conduct a one-tailed test, for whether the observed mean deviation for murders is greater than the mean deviation for our "placebo", accidents and illnesses. This test yields a p value of 0.195. Despite not reaching conventional levels of statistical significance, this provides some evidence of the strength of the relationship between markets and violence. Despite whatever plausible rationales there may be linking accidents and illnesses to

[6] We calculate the percentage of excess concentration compared to random as $\frac{\int_0^R (\hat{K}_{obs}(r) - \hat{K}_{pois}(r)))dr}{\int_0^R (\hat{K}_{pois}(r)))dr} \cdot 100$.

hubs of economic activity, the connection between violence and the marketplace remains stronger. While this provides some empirical evidence for our model's first prediction, after unpacking the mechanisms underpinning this relationship we proceed to a plausibly-causal analysis of the same flavor.

3.4 Motives and Mechanisms Linking Murders and Marketplaces

As a mean of assessing the mechanisms linking marketplaces to violent behavior, we turn to towards the Coroner's accounts of these 14th century homicides (Eisner, 2023). These accounts represent a summary written by the Coroner's clerks of the details of each murder as drawn from testimonies of a hastily assembled investigative jury (Sharpe, 1913). We employ a locally hosted large-language model (LLM), a 32 billion parameter distillation of the open-source DeepSeek-R1, to analyze the texts. The use of open-source LLMs is paramount to ensure that data used in the analysis does not "leak" into the training dataset of closed LLMs (Ludwig, Mullainathan and Rambachan, 2025)[7]. DeepSeek-R1 is a relatively new open-source LLM that has been shown to match or outperform other popular models and humans in reasoning tasks (Guo et al., 2025).[8] Leveraging a locally hosted LLM helps to ensure the reproducibility of our findings. We are able to seed our results and set the LLM temperature parameter (a parameter governing the stochastic nature of the model's token selection) to zero, which has been shown to result in the greatest consistency for LLM output (Blackwell, Barry and Cohn, 2024).

We prompt this locally hosted LLM to act as a detective and identify whether the likely motive behind the murder in question was related to business activity, employment, or trade. The LLM is further prompted to provide a brief rationale of the linkage if it answered in the affirmative. After assessing all of the murders, the model is prompted to identify four common themes across the motives of those murders that it tied to economic activity. In a final stage, the LLM rereads the Coroner's accounts and, for the murders that it previously labeled as related to business activity, assigns to each one of its four generated themes. All of our prompting consists of zero-shot prompting rather than the chat based prompting styles that are common in most online LLM chat interfaces (Wei et al., 2022). The structure of our prompts can be found in the appendix.

Across the 149 medieval homicides analyzed, the LLM identified 39 as being likely motivated by business activity. The LLM identified the following common themes across those murders: workplace disputes, trade rivalries, business-related theft, and inter-trade conflicts. Predictably, violence arose from crimes targeting businesses and from common disputes and arguments among co-workers. However, perhaps more interestingly, competition between individuals in the same trade seems to have been a substantial driver of violence. Across our data there are eight murders that can plausibly be attributed to a trade rivalry motive. All are cases in which both victim and perpetrator were engaged in the same profession. The Coroner's Accounts record arguments proceeding the violence, that could potentially be reflective of disputes over

[7] Closed LLMs include, but are not limited to, OpenAi's GPT and o1 family of models and Anthropic's Claude models that can only be accessed through controlled chat interfaces or the companies' own APIs.

[8] Notably, the 32 billion parameter distillation employed here outperforms all other tested similarly sized models in reasoning tasks (Guo et al., 2025).

customers or resources.

Another interesting identified common theme across the murders is conflict between trades. Guilds were powerful and influential forces in the middle ages (Ogilvie, 2014). Rivalries among the guilds of similar professions and competition between guilds to extend their influence and the limits of their exclusive privileges often led to conflict (Ogilvie, 2014). A prime example of this from the data used here is the 1325 murder of a man of the saddlers' guild by men of the goldsmiths' guild looking for rivals to attack in the street. However, violence between trades was not limited to that backed by powerful guilds. Often, simply the work of multiple professions in close proximity gave way to disputes that could arise to violence. The work of one profession could interfere with the work of another. As an example, we can look towards the 1326 murder of an eel seller. When the eel seller spilled a bucket containing eel skins outside of a merchant's shop, the merchant and his apprentice beat him to death. Such merciless violence arose from a routine dispute, driven by the close proximity in which such diverse professions existed.

The homicides of the era's marketplaces arose from petty theft and routine disputes. Theft can be deterred and disputes can be mitigated before they arise to the point of violence. Much of what we see having spurred violence in the markets of medieval London was born from the absence of strong formal institutions to prevent it. In our conceptual framework we have held that that violence can arise from routine criminal activity and from disputes and interpersonal conflicts getting out of control. Our framework leads to a simple prediction. An institution that is able to either increase the probability that norm or law violations result in sanctions or is able to function in some greater capacity as an arbitrator of disputes would reduce levels of violence by reducing the rate at which routine conflicts escalate. We proceed to an empirical test of this prediction, demonstrating with plausibly-causal evidence that the introduction of such an institution does reduce the levels of violence observed around the marketplace.

4 The Role of Enforcement and Dispute Resolution on Marketplace Violence

We have shown that violence and marketplaces are inextricably linked to one another. Our argument hinges on both disputes and routine criminal activity, which both have the potential to arise to violence, being more frequent in marketplaces. In our conceptual framework we have made two further potentially testable conclusions that arise from this relationship. Namely that $\frac{\partial V_{it}}{\partial p_i} < 0$ and $\frac{\partial V_{it}}{\partial \alpha} < 0$. We expect to see levels of violence decreasing with increases in the probability of facing enforcement effort and with increasing levels of arbitration/dispute resolution opportunity. The latter of the these two conclusions is directly testable. In the context of our empirical approach, these conclusions would hold that $\frac{\partial pr(\mathbb{1}(d_{i_k,j_l}<r)=1)}{\partial \alpha} < 0$ and $\frac{\partial pr(\mathbb{1}(d_{i_k,j_l}<r)=1)}{\partial p_i} < 0$. The probability of observing violence at a given radius from a market decreases with the presence of arbitration opportunity and the probability of an offender facing penalties.

The London Metropolitan Police Act of 1829 provides an opportunity to empirically test the inverse relationship between arbitration opportunity and the marketplace violence prediction of the model. The introduction of the Metropolitan Police Force in London would represent an increase in the probability of criminals facing enforcement effort and an increase in the presence of arbitration opportunities to mitigate the escalation of disputes.[9] Thus, because of the police's impact on the probability of criminals facing enforcement effort, it should be expected that following the introduction of the police force, violence decreases in areas subject to their jurisdiction. This would represent a decrease in the overall intensity. However, because of police further representing a potential arbitrator of disputes, increasing the overall level of arbitration available to participants in disputes, we should expect for levels of violence to decrease *more* in marketplaces than in non-market areas. This arises from our previous assumption that $\mu_M > \mu_{-M}$; disputes occur more regularly in the vicinity of markets. Thus, increasing levels of arbitration/dispute resolution opportunity would result in a changing in the underlying spatial point process, as violence is reduced *more* in the vicinity of markets where the impact of the change in arbitration opportunity is felt more acutely.[10]

Thus, we can predict that the introduction of the London Metropolitan Police would lead to a situation in which violence decreases in all areas subject to the newly formed police jurisdiction (a reduction in intensity) due to the increased probability of facing penalties, while violence decreases more so in marketplace areas due to the police's ability to arbitrate disputes (a shift in the spatial point process leading to a reduction in spatial concentration). We can expect to see a shrinking in levels of violence in the marketplaces that are subject to the new police force's jurisdiction relative to those that are not. Variation in marketplace locations with respect to the London Metropolitan Police Force's jurisdictional boundaries will allow us to test this conclusion empirically. The next subsection illustrates our identification strategy in more detail.

4.1 Identification and Empirical Strategy for Old Bailey

Here, we seek to test our conceptual framework's prediction that the introduction of a police force would lead to a lessening of the concentration of violence around marketplaces. From our conceptual framework, we have come to the conclusion that levels of violence in marketplaces exposed to an increase in arbitration opportunities should see decreases in violence relative to markets that see no change in arbitration opportunities. The introduction of the London Metropolitan Police Force in 1829 provides an ideal setting to test this prediction.

The creation of the London Metropolitan Police has been studied in depth, and treated as a natural experiment, by Bindler and Hjalmarsson (2021), who examined the impacts of this early professional police force on crime by comparing crime outcomes in the new force's jurisdiction to those outside of their jurisdiction, finding a decrease in violent crime. McCannon and Porreca (2025) show that the police force's

[9](Newell, 2016, p. 173) discusses how by the mid-19th century professional police forces began to interfere heavy-handedly in fights and disputes among the lower classes.

[10]In making this argument, we are for simplicity introducing an additional assumption that $\frac{\partial v^D(D_{it})}{\partial p_i} = \frac{\partial v^C(C_{it})}{\partial p_i}$. Changes in the probability of offenders facing enforcement effort impacts the levels of violence arising from dispute escalation and routine crime escalation in the same manner. Our conceptual framework also holds that the rate at which routine disputes arise to violence is a function of the same "enforcement probability" variable impacting the crime to violence channel. In the interest of generality and simplicity, we do not explore this in detail. However, if $\frac{\partial v^D(D_{it})}{\partial p_i} < \frac{\partial v^C(C_{it})}{\partial p_i}$, i.e enforcement probability impacts the dispute escalation channel more acutely, then we would similarly expect the introduction of a police force to reduce violence in marketplaces more than in the rest of the jurisdiction.

introduction did not lead to changes in conviction rates across London as whole. Here, we look specifically at changes in the *concentration* of homicides around marketplaces of the era, exploiting the historical fact that the City of London, a particular central district within the broader city that has held a unique status for historical reasons, was not under the jurisdiction of the London Metropolitan Police Force and did not receive its own police force until 1832, three years after the London Met Police's birth (Stark, 1931, p. 12). [11]

Due to this peculiarity of jurisdiction we are able to test for differential changes in the spatial concentration of homicides in market areas under the Met Police's jurisdiction and those that are not, before and after this police force debuted. This is a bit different than the Bindler and Hjalmarsson (2021) design, in which the authors primarily exploited the fact that the Met's jurisdiction also initially ended at a 7 mile radius from Central London. The identification strategy we employ herein is nested within their framework, but zooms in on the smaller discontinuity of jurisdiction present in central London due to the fact that none of the era's recorded markets were outside of the 7 mile radius.

To test the prediction from our conceptual framework that a shrinking in the levels of violence near marketplaces under the new police's jurisdiction should be observed, we develop a novel empirical estimator that we term as *difference-in-differences in spatial concentration.* Due to the lack of clear boundaries as to what exactly constitutes a market area, we extend the mean-deviation descriptive statistic for cross-type K functions introduced in the prior section to settings in which spatial concentration is the outcome of interest in a policy experiment. This estimator is akin to the original two by two difference-in-differences estimator of Card and Krueger (1994). These sorts of two by two difference-in-differences estimators were detailed in depth in Goodman-Bacon (2021). In general these estimators are the difference between the pre/post differences for treated and control units. Our estimator takes the following form:

$$\hat{\tau}_{DiD} = (\theta_{post}^{Met} - \theta_{pre}^{Met}) - (\theta_{post}^{Non\ Met} - \theta_{pre}^{Non\ Met}) \tag{4}$$

Here, the θ parameters represent the the mean deviation statistics, described in Equation 3, computed for different groups. These parameters are calculated for markets either within or outside of the new police force's jurisdiction in the pre or post period. Under the assumptions (akin to typical difference-in-differences designs) that a) spatial concentration of murders around markets would have evolved similarly for both City of London and Met jurisdiction markets in the absence of the jurisdictional change, and b) changes in concentration in areas now under the Met Police's jurisdiction do not induce changes in the *concentration* of murders around markets in the City of London area, then the $\hat{\tau}_{DiD}$ parameter can plausibly identify the causal impact of the Metropolitan Police's birth on the spatial concentration of murders around markets.

The first of these assumptions is akin to the parallel trends assumption in classical difference-in-differences

[11] 1832 marks the beginning of the City Day Police and the Nightly Watch. By the end of 1838, these two groups had merged into one, and the City of London Police Act was finalized in 1839. In the appendix we replicate our primary analysis, with a wider time window to reflect the possibility that City of London could potentially be considered "untreated" until that 1839 Act (City of London Archives, 2021).

designs. Its aim is to ensure that the pre/post difference for the control group provides an appropriate counterfactual for the treated set. Unfortunately, for our context, the data at our disposal precludes formal testing of this assumptions with methods similar to those used in typical DiD designs. We do not have enough pre-treatment period data to generate alterative spatial planes of homicides to formally test the evolutionary trajectories of spatial concentrations across times for both groups. While such an analysis would be preferred for future work seeking to employ this same sort of estimator, here we simply rely on the historical context. There are no other policy changes in this time period (1826-1831) that would differentially impact the City of London and the metropolitan area in such a way that spatial concentration of crime would be expected to evolve differently for the two groups.[12] Formally, this assumption can be expressed as:

Assumption 1:

$$\mathbb{E}[\theta_{it}(0)|\alpha = 1] - \mathbb{E}[\theta_{it-1}(0)|\alpha = 1] = \mathbb{E}[\theta_{it}(0)|\alpha = 0] - \mathbb{E}[\theta_{it-1}(0)|\alpha = 0]$$

In the above notation, $\mathbb{E}[\theta_{it}(0)|\alpha = 1]$ represents the expectation of the potential outcome for unit i in time t of group $\alpha = 1$ in the absence of treatment status. The assumption states that in the absence of treatment, the evolution for both groups, $\alpha = 0$ and $\alpha = 1$, would be equivalent across time.

The second assumption is akin to the stable unit treatment value assumption (SUTVA) of Rubin (1980). SUTVA requires that there are no "spillovers" between treated and control groups- that treatment does not impact untreated groups in the outcome of interest. In our context, this would require that the formation of the new police force does not cause the spatial *concentration* of homicides around marketplaces to change in areas outside of their jurisdiction. Formally this assumption can be expressed as:

Assumption 2:

$$\mathbb{E}[\theta_{it}(0)|\alpha = 0] = \mathbb{E}[\theta_{it}(1)|\alpha = 0]$$

Formally this states that the potential outcome for untreated observations is equivalent to the observed outcome. Only treatment status impacts the expectation. This "no spillover" assumption is a bit less straightforward in our setting than in more typical causal inference designs. The key to defending this assumption here is that SUTVA will only be violated if concentration changes in the untreated areas, not simply if counts of incidents change. Because both the true K function, its estimator, and the random point processes they are compared to are scaled by the intensity of the underlying point process (in this case homicides), a spillover resulting in displacement of violence and an increase in homicides in the area outside of the new police force's jurisdiction would not induce a change in the concentration unless the spillover were to induce a change in the spatial pattern of the homicides. The intensity of homicides in the untreated area can increase or decrease as a result of spatial spillovers without impacting our concentration measure of interest, as long as that spillover does not change the underlying pattern or spatial point process by which those homicides are distributed.

[12] See McCannon and Porreca (2025) for a review of some of the numerous changes to the criminal justice system that did occur during this era.

Our spatial concentration curve as defined in equation (2) is a function of the overall homicide intensity across the city, λ_j, and the localized homicide probability, $pr(\mathbb{1}(d_{i_k,j_l} < r) = 1)$. If the police force, as predicted, drives down levels of violence then this would mechanically induce a downward shift in homicide intensity across the city (less homicides being divided across the same spatial extent). However, the area in which these reductions are localized would see the downward shift in $pr(\mathbb{1}(d_{i_k,j_l} < r) = 1)$, leading to an overall downward movement in our measure of concentration. One could anticipate that a potential SUTVA violation would arise if homicides shift from markets in treated areas to markets in untreated areas. This exact movement should be expected, as we have argued in our conceptual framework that homicides in part arise from routine criminal activity which is readily displaced by changes in enforcement effort. If there is only one intensity measure for the entire city, the displacement of homicides induces no change in the overall homicide intensity, but does increase $pr(\mathbb{1}(d_{i_k,j_l} < r) = 1)$ in the areas in which the homicides are displaced to, in turn increasing the measure of spatial concentration for that "control" area and violating the no-spillover assumption.

However, the potential SUTVA violation is avoided in the framework of our estimator by splitting the city into treated and untreated study windows. Intensity is estimated separately for both groups allowing for an increase in intensity to offset the corresponding increase in $pr(\mathbb{1}(d_{i_k,j_l} < r) = 1)$ for the areas that displacement occurs to. Thus, as long as the pre-displacement spatial pattern of outcomes is unchanged, then the increase in count will not change measures of concentration for the control group.

With this notation and our assumptions in hand, we will proceed to a brief formal derivation of this estimator.

4.1.1 Derivation of the Estimator

We are interested in estimating the average treatment effect on the treated, the ATT. The group receiving treatment is denoted $\alpha = 1$, treatment is received in period t. $\theta_{it}(1)$ represents an observed value, while $\theta_{it}(0)$ represents an unobserved counterfactual. We can thus define our target estimand, the ATT, as:

$$\hat{\tau} = \mathbb{E}[\theta_{it}(1)|\alpha = 1] - \mathbb{E}[\theta_{it}(0)|\alpha = 1] \tag{5}$$

The latter term represents the unobserved counterfactual state of the world, in which our treated units do not receive treatment. We can rearrange our parallel trends assumption from above (Assumption 1) to yield an expression equivalent to that counterfactual.

$$\mathbb{E}[\theta_{it}(0)|\alpha = 1] = \mathbb{E}[\theta_{it}(0)|\alpha = 0] - \mathbb{E}[\theta_{it-1}(0)|\alpha = 0] + \mathbb{E}[\theta_{it-1}(0)|\alpha = 1] \tag{6}$$

We can now reintroduce our SUTVA assumption (Assumption 2), namely that treatment can only impact treated units, to replace unobserved counterfactual values from that expression with their observed real world equivalents. This is due to the fact that the assumption holds that untreated units and their "counterfactual" potential outcomes are the same. Thus, our unobserved counterfactual state of the post-treatment period outcomes for treated units in the absence of treatment can be expressed solely as function of observed values as follows.

$$\mathbb{E}[\theta_{it}(0)|\alpha = 1] = \mathbb{E}[\theta_{it}(1)|\alpha = 0] - \mathbb{E}[\theta_{it-1}(1)|\alpha = 0] + \mathbb{E}[\theta_{it-1}(1)|\alpha = 1] \tag{7}$$

This is then substituted back into our original expression of the ATT target estimand, which after some rearranging yields the following expression, reminiscent of the common two by two difference in differences estimator.

$$\hat{\tau} = (\mathbb{E}[\theta_{it}(1)|\alpha = 1] - \mathbb{E}[\theta_{it-1}(1)|\alpha = 1]) - (\mathbb{E}[\theta_{it}(1)|\alpha = 0] - \mathbb{E}[\theta_{it-1}(1)|\alpha = 0]) \tag{8}$$

When estimated, this takes the form of equation 4.[13]

4.2 Data

In estimating this mode, we utilize an entirely separate set of data sources. For the locations of crimes in Georgian England we make use of the replication data from Bindler and Hjalmarsson (2021). This data includes crimes reported to police and tried (including guilty pleas) at the Old Bailey courthouse (see Bindler and Hjalmarsson (2018, 2019, 2020) and McCannon and Porreca (2025) for more background information about *The Old Bailey Proceedings* from which this data is drawn, along with discussion of the consistency of reporting in that data). Notably, Bindler and Hjalmarsson (2021) makes the case that the introduction of the Metropolitan Police Force did not impact reporting or clearance rates and that serious crimes, such as homicides, were consistently reported across time. Most importantly for our purposes, the authors geocoded these crimes based upon information found in the *Proceedings*. This data covers the years 1821-1837. We limit our focus to crimes listed as homicide or manslaughter, of which there are 258.

We draw our list of marketplaces of the era from Smith (1999).[14] We rely upon his list of the formal marketplaces of London in 1840. Our results do not substantially change when including his list of "unofficial street markets". However, for the results reported here we choose to focus on the author's primary list of 28 markets, as they are all centrally located within the boroughs that constitute central London so as to avoid concerns regarding fundamental differences between the locations of the markets that we are comparing.[15] We proceed to geolocate those locations and map them alongside our murders.

[13] We would like to note that as with other two by two difference-in-differences estimators, this new estimator for spatial concentration can be readily adapted to multiple time periods, multiple groups, or staggered treatment timing using the same arguments as other papers found elsewhere in the difference-in-differences literature. These extensions are outside of the scope of the current work, as this is aimed at being an applied study. However, these extensions and their applications may prove valuable for future researchers working across diverse topics.

[14] Smith (1999) is a PhD thesis. See Smith (2002) for a published paper by the same author based upon that work.

[15] It also bares noting that we are using a *within* estimator. We are comparing changes in the same areas over a quite small time window. Immutable differences between the locations of markets are captured by the within-unit differencing that is a component of the estimator.

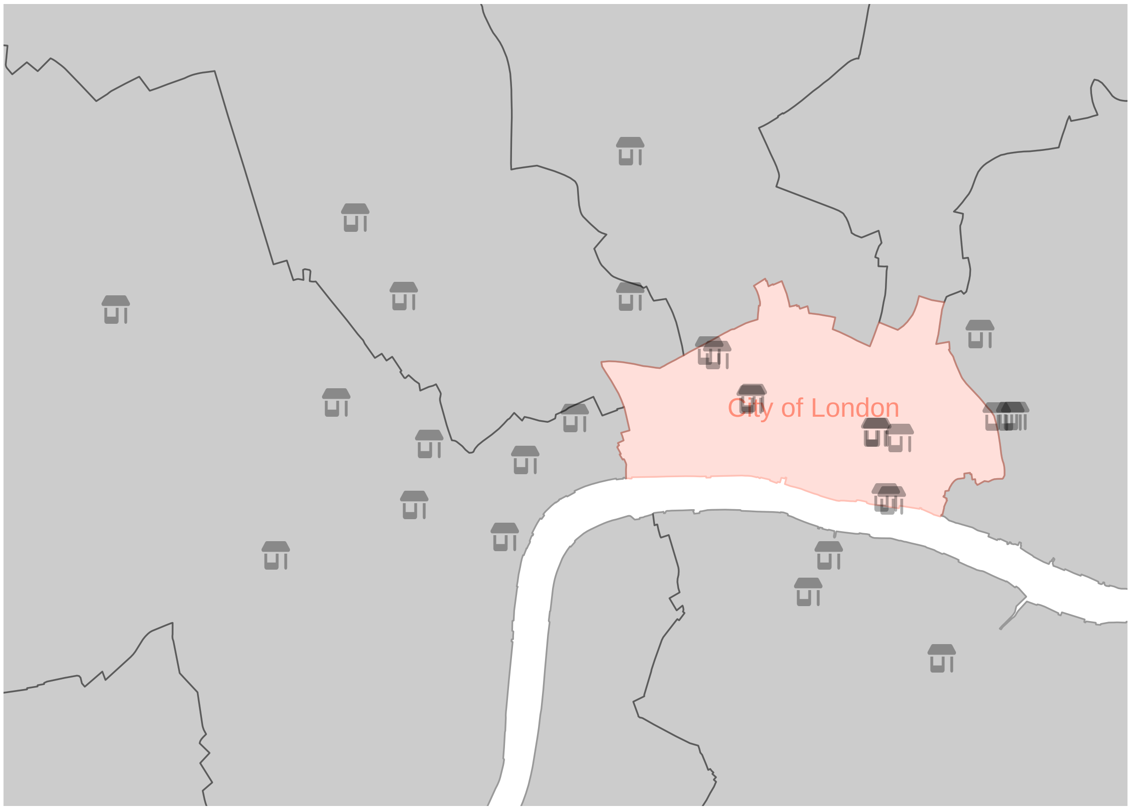


Figure 3: Figure depicting the locations of London marketplaces inside both the City of London (in pink) and the Metropolitan London (in gray).

The final component of the data used in this section is the GIS file for the City of London. The City of London boundaries were remarkably consistent from the middle ages on. However, they were slightly changed in 1993. To our knowledge no preexisting digital GIS maps of the pre-1993 boundaries are available. As such, we made use of the map of the boundary changes published alongside the adopted statute to manually shift the boundaries of the existing post-1993 GIS files to more accurately mirror the prior boundaries of the City of London for our time period of interest (Her Majesty's Stationery Office, 1993).[16] Our results do not change when using the modern map of City of London.

4.3 Results

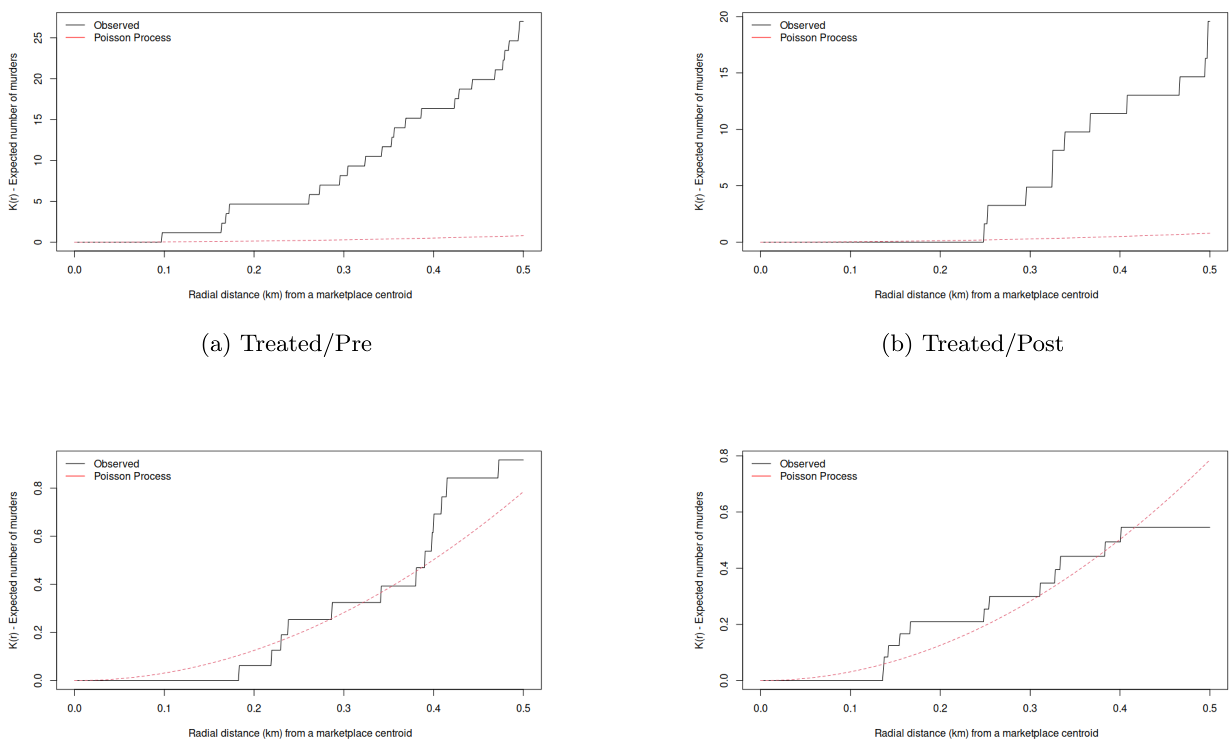
We estimate the impact of the introduction of the London Metropolitan Police as described in the above section. We construct an estimate of the variance of this aggregated treatment effect parameter using basic properties of variance addition as follows. We detail the derivation of the functional form for the covariance

[16]For the purposes of generating the maps displayed in the paper, we used modern shapefiles of London's boroughs and the City of London. This simplification was done to maintain the borders with other boroughs so as to create a cleaner looking map. Our calculations show that the 1993 change in boundaries represented a less than 5% increase in the area of City of London. The shapefiles used for mapping contemporary metropolitan London and the City of London's boundaries within were taken from the Statistical GIS Boundary Files housed in the datastore from the Mayor of London's Greater London Authority. These shapefiles can be found at https://data.london.gov.uk/dataset/statistical-gis-boundary-files-london. We used the MSOA 2021 files.

components and their estimation in the appendix.

$$\begin{aligned}
\sigma^2_{\hat{\tau}_{DiD}} &= \sigma^2_{\theta^{Met}_{post}} + \sigma^2_{\theta^{Met}_{pre}} + \sigma^2_{\theta^{NonMet}_{post}} + \sigma^2_{\theta^{NonMet}_{pre}} \\
&\quad - 2cov(\theta^{Met}_{post}, \theta^{Met}_{pre}) - 2cov(\theta^{NonMet}_{post}, \theta^{NonMet}_{pre}) \\
&\quad + 2cov(\theta^{Met}_{post}, \theta^{NonMet}_{post}) + 2cov(\theta^{Met}_{post}, \theta^{NonMet}_{pre}) \\
&\quad + 2cov(\theta^{Met}_{pre}, \theta^{NonMet}_{post}) + 2cov(\theta^{Met}_{pre}, \theta^{NonMet}_{pre})
\end{aligned} \tag{9}$$

The figure below plots the individually estimated Ripley's K curves and the homogeneous Poisson process curves that they are compared to.[17]



(a) Treated/Pre

(b) Treated/Post

(c) Control/Pre

(d) Control/Post

Figure 4: Grid depicting the individual Ripley's K estimates (and associated homogeneous Poisson processes) that together are used to construct the aggregated difference-in-differences parameter.

We limit our data to the period from 1826-1831, to provide a balanced time window of three years before and after the 1829 birth of the new police force.[18] This procedure yields an estimate of -5.36 for our $\hat{\tau}_{DiD}$ parameter, with a t statistic of 1.687 and a p value of 0.093. This represents a 54.3% reduction in the concentration of homicides around marketplaces. While the areas subject to the London Metropolitan

[17] It is notable that there is almost no excess concentration of violence around the markets of our control group City of London. In fact there is very little violence in this area at all despite its centrality within the city. To address concerns that the inequality in spatial window sizes, particularly the smaller window employed for City of London, is deflating the K curve for our control, in the appendix we replicate this result with a single spatial window shared for both groups.

[18] Across this period there are 94 homicides in our data.

Police's jurisdiction experienced a large-scale reduction in the concentration of violence around markets, consistent with the predictions of our empirical framework, no change in concentration was observed in the areas that remained outside of their influence. As discussed in our preceding identification section, under our established assumptions this estimated impact is able to be attributed to the increased dispute resolution capacity brought forth by the London Metropolitan Police Force- evidence in support of the conceptual framework we have developed linking markets and violence.

5 Conclusion

Throughout this paper we have tried to make the case that the factors that link the markets for illegal commodities to violence are not unique to those markets, or in the least have historically existed across a broader swath of markets. The factors driving violence in the markets for illicit narcotics, for example, are not altogether unique to the commodities being sold. Goldstein (1985) attributes much of violence in illicit drug markets to predation, disputes, and competition. We make the argument that these same factors are intrinsic to all markets, but it is the presence of strong institutions of enforcement and dispute resolution that prevent violence from being as ubiquitous of an outcome elsewhere.

To this end, we have developed a conceptual framework to elucidate the pathways linking violence and markets. Using a historical dataset new to the economics literature we have shown that in the middle ages, a period long before the formalization of most institutions that would eventually be able to quell routine crime and violence, there was an excessive concentration of violence around marketplaces. Using a locally hosted large language model, we probed the motives of these homicides to explore the mechanisms governing the spatial distribution of medieval violence, finding that much of the violence associated with economic activity would have been preventable if more developed means of dispute resolution had been available.

We went on to test that conclusion directly. To this end, we jumped forward in time several hundred years to Georgian England to examine how the birth of London's first professional police force, an institution able to both deter crime and arbitrate disputes, impacted the concentration of violence around markets. Intent on exploiting geocoded crime data from the era made available by Bindler and Hjalmarsson (2021) and the peculiarities of the newly created police force's jurisdiction, we derived a novel difference-in-differences estimator for spatial concentration. We argue that because of this new estimator's properties and the assumptions underlying its derivation that we are able to exploit this force's formation to identify the impact of the increased dispute resolution capacity on the concentration of violence around markets. We find that in areas subject to this new police force, the degree to which violence was concentrated around markets fell by over 50%.

Altogether, we argue that the weight of this evidence suggests that trade in the marketplace intrinsically breeds conditions that have the potential to give birth to violence. In many ways this result mirrors that seen in García-Jimeno (2016), in which the criminalization of a formerly normalized commodity led to increased levels of violence around its trade. We argue that it is not the nature of the illegal goods that are traded that breeds violence, but rather the lack of access to formal institutions of enforcement and dispute resolution that allows competition to grow deadly.

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A Appendix

A.1 Computing the Variance of Combinations of Mean Deviation Statistics

Here we present the basic derivation of the variance for combinations of the mean deviation statistics that we employ throughout this paper. Here we present the basic formulation, as used in our placebo exercise in the paper's first section. However, the same principle can be extended to combinations of more than two mean deviations (as in our difference-in-differences design). The basic formulation of the combined variance is:

$$\sigma^2_{\theta_1-\theta_2} = \sigma^2_{\theta_1} + \sigma^2_{\theta_2} - 2cov(\theta_1, \theta_2) \tag{10}$$

The variances for the individual mean deviations are computed using the spatial bootstrap estimator of Loh (2008). The covariance of the two mean deviations takes a basic structure as follows:

$$cov(\theta_1, \theta_2) = \mathbb{E}[\theta_1\theta_2] - \mathbb{E}[\theta_1]\mathbb{E}[\theta_2] \tag{11}$$

Using the mean deviation formula presented in equation (3), we can express the product of two mean deviations as:

$$\theta_1\theta_2 = \left(\frac{1}{R}\int_0^R (\hat{K}_1(r) - \hat{K}_{pois,1}(r))dr\right)\left(\frac{1}{R}\int_0^R (\hat{K}_2(r) - \hat{K}_{pois,2}(r))dr\right) \tag{12}$$

We proceed to take the expectation and simplify:

$$\mathbb{E}[\theta_1\theta_2] = \mathbb{E}\left[\frac{1}{R}\int_0^R (\hat{K}_1(r) - \hat{K}_{pois,1}(r))dr \frac{1}{R}\int_0^R (\hat{K}_2(r) - \hat{K}_{pois,2}(r))dr\right] \tag{13}$$

Since the radii considered are the same (in all cases considered in this paper), we can simplify even further:

$$\mathbb{E}[\theta_1\theta_2] = \frac{1}{R^2}\int_0^R \mathbb{E}\left[(\hat{K}_1(r) - \hat{K}_{pois,1}(r))(\hat{K}_2(r) - \hat{K}_{pois,2}(r))\right]dr \tag{14}$$

The integrand of the above equation is equivalent to the covariance of $\hat{K}_1(r)$ and $\hat{K}_2(r)$:

$$\mathbb{E}[(\hat{K}_1(r) - \hat{K}_{pois,1}(r))(\hat{K}_2(r) - \hat{K}_{pois,2}(r))] = cov(\hat{K}_1(r), \hat{K}_2(r)) \tag{15}$$

We are able to directly compute this covariance. We detail this procedure shortly.

$$\mathbb{E}[\theta_1\theta_2] = \frac{1}{R^2}\int_0^R cov(\hat{K}_1(r), \hat{K}_2(r))dr. \tag{16}$$

Continuing to simplify our main $cov(\theta_1, \theta_2)$ expression, because $\mathbb{E}[\hat{K}_i(r)] = \mathbb{E}[\hat{K}_{pois,i}(r)]$ we can continue eliminating terms.

$$\mathbb{E}[\theta_i] = \frac{1}{R}\int_0^R \mathbb{E}[\hat{K}_i(r) - \hat{K}_{pois,i}(r)]dr = \frac{1}{R}\int_0^R \mathbb{E}[\hat{K}_i(r)] - \mathbb{E}[\hat{K}_{pois,i}(r)]dr = 0 \tag{17}$$

Thus we are left with our final, and directly estimable, form of the covariance.

$$cov(\theta_1, \theta_2) = \frac{1}{R^2}\int_0^R cov(\hat{K}_1(r), \hat{K}_2(r))dr \tag{18}$$

We estimate $cov(\hat{K}_1(r), \hat{K}_2(r))$ pointwise, constructing a vector of local covariances along the $\hat{K}_i(r)$ curves. We take neighborhoods of 10 points centered around each individual point to construct local covariances between the two curves in each neighborhood.[19] Within each neighborhood, s, the local covariance is computed as:

$$cov_s(\hat{K}_1(r), \hat{K}_2(r))(r_i) = \frac{1}{S}\sum_{i}^{i+s}(\hat{K}_1(r)_i - K_1\bar{(r)}_w)(\hat{K}_2(r)_i - K_2\bar{(r)}_w) \tag{19}$$

Here, we are taking the average covariance across a window of size s between the two curves, where the means used for comparison are local means for that window. We use this local covariance for each point that falls within the window, as to end with a vector of local covariances equal in length to the underlying $\hat{K}_i(r)$ curves. This can then be integrated over to provide our specific mean deviation covariances.

A.2 Examples of LLM Prompts

A.3 Concentration of LLM Labeled "Business-related" Homicides

A.4 Alternative Time Window for DiD

A.5 Including Informal Street Markets in DiD

A.6 DiD with a singular Spatial Window (ignoring SUTVA)

A.7 DiD with modern City of London as untreated area

[19] These neighborhoods are smaller at the ends of the curves when there are not enough points before or after. Our minimum neighborhood size is 5 points.