Measuring *Marginal* Crime Concentration: A New Solution to an Old Problem *

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Abstract

Objectives: In his 2014 Sutherland address to the American Society of Criminology, David Weisburd demonstrated that the share of crime that is accounted for by the most crime-ridden street segments is notably high and strikingly similar across cities, an empirical regularity referred to as the "law of crime concentration."

Methods: Using data from three of the largest cities in the United States, compare observed crime concentration to a counterfactual distribution of crimes generated by randomizing crimes to street segments. We show that this method avoids a key pitfall that causes a popular method of measuring crime concentration to overstate the degree of crime concentration in a city.

Results: Most (but not all) crimes are concentrated amongst a small number of hot spots but the precise relationship is weaker — sometimes considerably so — than has been documented in the empirical literature. Within a city, crime is least concentrated in the neighborhoods that experience the largest number of crimes. The law of crime concentration sometimes holds only tenuously in the communities in which crimes are most prevalent.

Conclusions: The method we propose is simple and easily interpretable and compliments recent advances which use the Gini coefficient to measure crime concentration.

Keywords: Criminology of place, hot spots, microgeography, Law of crime concentration

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1 Introduction

A large and growing literature in criminology documents the importance of place — in particular, microgeographic places like street segments — one of the two faces of a standard city block — in explaining crime. Across a large number of places and in a variety of contexts, crime is found to be highly concentrated (Sherman et al., 1989; Eck et al., 2007; Weisburd, 2015; Andresen et al., 2017) and persistent over time (Weisburd et al., 2009; Gorr and Lee, 2015). Taken as a whole, the substantial geographic concentration of crime suggests that the social and physical features of the urban landscape might potentially play an important role in the crime production function and therefore that crime hot spots are an appropriate target over which a social planner can focus resources and ultimately intervene.[1]

In his 2014 Edmund H. Sutherland address to the American Society of Criminology, David Weisburd summarized the research on the importance of place and noted that places have been studied far less by criminologists than other natural units of analysis (Weisburd, 2015). Weisburd further notes the extent to which crime is concentrated among the most crime-ridden street segments is remarkably consistent across cities and proposes that this empirical regularity is sufficiently strong to be characterized as a "law of crime concentration."[2] Across eight cities of varying sizes, the top one percent of street segments, ranked by crime incidence, accounted for approximately 25 percent of crimes in that city and the top 5 percent of street segments accounted for half of the crimes. The stability of these estimates is noteworthy and forms the basis for the claim that this pattern can be characterized as a law.

Despite the abundance of research inspired by the law of crime concentration, recent scholarship has raised a number of key measurement issues in how crime concentration should actually be measured (Bernasco and Steenbeek, 2017; Hipp and Kim, 2017; Levin et al., 2017; Prieto Curiel, 2019; OBrien, 2019; Mohler et al., 2019). In particular, past research notes that the fact that a small share of street segments accounts for a large share of the crime over a given time period does not necessarily mean

[1] Indeed, the empirical regularity that crime is highly spatially concentrated has been central to the study of criminal justice policy and has promulgated a number of important research literatures that have become a mainstay of empirical criminology including a large literature on hot spots policing (Weisburd and Green, 1995; Sherman and Weisburd, 1995; Braga, 2001; Braga and Bond, 2008; Weisburd and Telep, 2014; Braga et al., 2014) and the equally important literature on the importance of environmental design including research on restoring vacant lots (Branas et al., 2011; Garvin et al., 2013; Bogar and Beyer, 2016; Kondo et al., 2016; Branas et al., 2018; South et al., 2018; Moyer et al., 2019), reducing physical disorder (Kelling et al., 1982; Keizer et al., 2008; Skogan, 2012; Braga et al., 2015) and improving ambient lighting (Farrington and Welsh, 2002; Welsh and Farrington, 2008; Doleac and Sanders, 2015; Chalfin et al., 2019, 2020).

[2] In Weisburd's own words, "for a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages."

that crime is substantively concentrated. To see this, consider that even in the cities with most the challenging crime problems, the number of street segments far exceeds the number of crimes known to law enforcement over any reasonable time window. For instance, consider a city like New York in which there are approximately 120,000 street segments and 300 homicides annually. In this case, it is trivial to see that, even if each homicide occurs on a different street segment (thus, by definition, there would be no concentration of crime), 0.25 percent of the street segments would account for 100 percent of the homicides.[3] Thus, using the standard metric of crime concentration, the extent to which at least some types of crimes are concentrated will be biased upward. Similarly, the standard metric does not allow for a comparative analysis of concentration among different types of crimes since rarer crimes will, for mechanical reasons, appear to be more concentrated than more common crimes (Hipp and Kim, 2017).

Recent scholarship has proposed several modifications to the measurement of crime concentration that address these concerns (Bernasco and Steenbeek, 2017; Hipp and Kim, 2017; Levin et al., 2017; Curiel et al., 2018; Mohler et al., 2019; OBrien, 2019). A particularly common approach that is advanced by Levin et al. (2017) and which can be found in abundance in the recent literature (see e.g., Steenbeek and Weisburd (2016), Andresen et al. (2017), Schnell et al. (2017) and Umar et al. (2020)) is to measure crime concentration *only among street segments that experienced at least one crime.* The idea behind this approach is that crimes can only be concentrated where they, in fact, occur. This modification to the measurement of crime concentration does tend to reduce the degree of the bias in the standard measure but, as we show, in most empirical applications, removing crime-free street segments will continue to lead to a substantial overestimate of the extent to which crimes are concentrated.

In this article, we propose a different way to measure crime concentration that is simple, easily interpreted and which fully addresses the concerns outlined above. In particular, we compare actual concentration — for instance, the share of street segments accounting for 25 percent or 50 percent of the crimes — to a counterfactual level of crime concentration that is constructed by randomly assigning crimes to street segments, with replacement. Using randomization we generate a spatial distribution of crime where crime is not concentrated by construction.[4] Notably, our method compliments an alternative and highly convenient method of measuring crime concentration using the Gini coefficient (Bowers, 2014; Davies and Johnson,

[3]Even over a period of ten such years, if every homicide occurred on a different street segment, we would observe that just 2.5 percent of the street segments account for 100 percent of the homicides.

[4]Randomizing crimes to blocks yields a result that is substantively similar to allocating crimes using a Poisson distribution.

2015; Steenbeek and Weisburd, 2016; Bernasco and Steenbeek, 2017) while retaining one of the most attractive properties — the interpretability — of Weisburd's original metric.

Using our proposed metric and data from New York City, Chicago and Philadelphia, three of the five largest cities in the United States, we show that while most types of crimes exhibit considerable concentration, the degree to which crimes are actually concentrated is smaller than has been suggested by prior analyses. For common street crimes such as auto theft and robbery, we find that the law of crime concentration holds only to a limited degree. We further extend empirical testing of the law of crime concentration to police commands within cities, asking whether the law of crime concentration holds at the sub-city level. This analysis takes the perspective of a district commander in a police department who is charged with deciding how to allocate resources at the community level. We present new evidence that the law of crime concentration does not hold equally among neighborhoods. While crime is highly concentrated in the safest neighborhoods, the highest crime communities — those which receive the greatest amount of police resources and which are in the greatest need of effective intervention strategies — are precisely the neighborhoods in which crimes are *least* concentrated.

2 Prior Literature

2.1 Empirical Evidence on Crime Concentration

As noted by Weisburd (2015), the term "criminology of place" can be traced back to a 1989 article in *Criminology* by Sherman et al. (1989) which was among the first endeavors to systematically measure the concentration of crime among microgeographic areas.[5] However, the recognition that a large share of crime is clustered in a small share of places is an observation that is nearly as old as modern cities (Quetelet, 1831; Weisburd et al., 2009). Over the last few decades, a literature has proliferated to establish that micro- rather than macrogeography explains the lion's share of spatial variation in urban crime, (Steenbeek and Weisburd, 2016; Schnell et al., 2017), that crime is highly concentrated among a small number of crime hot spots (Eck et al., 2007; Weisburd, 2015) and that these hot spots, at least to an extent, persist over time (Weisburd et al., 2004, 2009; Gorr and Lee, 2015). Research has found that this pattern is not limited to low-impact crimes and applies equally, if not more forcefully, to some of the most costly criminal activity including gun crimes (Braga

[5] For a review of the historical development of the crime concentration literature, see Johnson (2010). For a review of theoretical work in this area, see Farrell (2015).

et al., 2010) and common street crimes such as robbery (Braga et al., 2010, 2011; Haberman et al., 2017)[6][7]

Since Weisburd's influential 2015 article, a rapidly growing literature, initiated by a 2017 special issue on the criminology of place in the *Journal of Quantitative Criminology*, has developed to further test and clarify the law of crime concentration and the extent to which it holds across time and place. Recent scholarship documents robust evidence that the law of crime concentration substantively holds in other U.S. cities including Chicago (Schnell et al., 2017), Seattle (Hibdon et al., 2017), St. Louis (Levin et al., 2017) and a large number of cities in California (Hipp and Kim, 2017), in a number of non-U.S. cities including Vancouver, Canada (Andresen et al., 2017) Milan, Italy (Favarin, 2018) and among various cities in the United Kingdom (Oliveira et al., 2017) and Latin America (Ajzenman and Jaitman, 2016) as well as in a suburban setting — Brooklyn Park, Minnesota (Gill et al., 2017). In every setting in which the law of crime concentration has been tested, the law, as proposed, holds up substantively.

2.2 Conceptual Challenges to Measuring Crime Concentration

As noted by Andresen and Malleson (2011), Levin et al. (2017), Hipp and Kim (2017), Bernasco and Steenbeek (2017) Curiel et al. (2018) and Mohler et al. (2019) among others, the chief challenge to using the standard concentration metric is that it will lead to upward biased measures of crime concentration when the number of places is large relative to the number of crimes. That is, when crimes are relatively rare, it will be true by definition that a small number of places will account for most or even all of the crimes in a city.[8]

The literature has proposed two main ways of dealing with this issue. First, researchers have proposed shifting to a different metric — the Lorenz curve or the closely related Gini coefficient — that is arguably better designed to measure the degree of inequality in a distribution (Bernasco and Steenbeek, 2017; OBrien, 2019; Mohler et al., 2019). A principal advantage of the Gini coefficient is that it allows researchers to characterize the relative degree of crime concentration using a single summary metric, without appealing to an arbitrary cutoff in the distribution of crimes (e.g., 25 or 50 percent of crimes). While the Gini coefficient can also per-

[6]Similarly, Hibdon et al. (2017) show that the law of crime concentration is substantively replicated when an additional data source — 911 calls for emergency service — are used to explore the concentration of illegal drug activity.

[7]These findings are subject to important criticisms regarding the measurement of crime concentration by Hipp and Kim (2017), Levin et al. (2017), Bernasco and Steenbeek (2017) and Curiel et al. (2018) which we discuss in Section 2.2.

[8]This issue is not merely academic since, in many cities, a large number of street segments do not experience crime over a given time period (Curman et al., 2015) and, as it turns out, this issue has enormous implications for the conclusions that are drawn about which crimes are concentrated and the extent to which they are. For instance, as noted in Hipp and Kim (2017), while the standard crime concentration metric suggests that violent crimes are more concentrated than property crimes, after correcting the problem identified above, there is clear evidence that the degrees of concentration among violent and property crimes are, in fact, similar.

form poorly when crimes are sparse, recent research (Bernasco and Steenbeek, 2017; OBrien, 2019; Mohler et al., 2019) has proposed effective ways to address this concern, thus providing a means of measuring crime concentration that is robust to the problem of crime-free street segments.[9] One limitation, however, in using the Gini coefficient is that it tends to be difficult to interpret, especially in communicating the degree to which criminal activity is concentrated to the wider world of criminal justice policymakers and researchers.[10] The Gini coefficient is, in our view, not very different from a correlation — it is an elegant and simple measure that is invariant to unit or scale — but it is difficult to communicate the cardinal information contained therein.

Given the inherent challenges in interpreting Gini coefficients, we argue that there remains a great deal of value in reporting crime concentration measures that correspond, as Weisburd proposed, to the share of places that account for a given share, typically one quarter or one half of crimes. Indeed, this remains a highly popular way to summarize crime concentration in the recent literature (Ajzenman and Jaitman, 2016; Gill et al., 2017; Andresen et al., 2017; Hibdon et al., 2017; Levin et al., 2017), sometimes alongside a Gini coefficient (Steenbeek and Weisburd, 2016; Schnell et al., 2017; Favarin, 2018; Vandeviver and Steenbeek, 2019; Umar et al., 2020).

Recent scholarship has proposed a second means of addressing issues caused by sparse crime data — while continuing to use Weisburd's original and highly interpretable crime concentration metric. The most popular solution in the literature which has been advanced in particular by Levin et al. (2017) is to measure the share of crimes that occur among the top k percent of street segments, limiting the data to *the street segments that experienced at least one crime*. The intuition behind such a correction is straightforward: since many street segments do not experience any crime at all, these zero crime street segments will tend to make crime appear more concentrated than it actually is at the top of the distribution. Accordingly, the proposal is to focus on the segments in which crimes do occur. By addressing bias in measures of crime concentration that is an artifact of crime-free places, this proposed metric purports to move us closer to correctly estimating the extent to which crime is substantively concentrated. To see how this might work, consider a city in which half of street segments do not receive crime. If 2 percent of all street segments account for one quarter of the crimes, then it will be the case that 4 percent of street segments *which experience non-zero crime counts* account for one quarter of the crimes. Thus, the standard concentration metric will be two times too small.

[9]Recent scholarship by Prieto Curiel (2019) raises questions about the stability of the Gini coefficient as well as the "modified Gini coefficient," noting that these are sensitive to changes in the underlying crime rate in a city.

[10]The Gini coefficient is formally defined as the ratio of the area between the Lorenz curve and the line of perfect equality, and the area above the line of perfect equality.

2.3 Substantive Issues with Removing Crime-Free Segments

There is some virtue to removing crime free street segments — it is simple, easy to compute and understand and it does, in some applications, help to address the statistical artifact caused by sparse crime data. However, as we demonstrate, this method will yield a metric of crime concentration that is biased upward – in some cases, considerably so. As we explain, the principal issue with this approach is that street segments which experience zero crimes is not the only reason why uniformity (k percent of segments account for k percent of crime) does not hold when crimes are assigned, at random, to street segments.

The implication of removing zero crime street segments to correct the non-uniformity problem is that, in the absence of any crime concentration, this measure of crime concentration should be 1. That is, the top k percent of street segments that have non-zero crime should account for exactly k percent of the crimes i.e., 25 percent of the street segments will account for 25 percent of the crimes, 50 percent of the street segments will account for 50 percent of the crimes, etc. This standard — that of uniformity — is an overly stringent standard that leads to an overestimate of the degree to which there is crime concentration. To see this, consider a simple example involving a city in which there are 1,000 street segments and 100 crimes. Using the standard measure of crime concentration, we would compute that $\frac{100}{1{,}000} = 10$ percent of street segments account for 100 percent of the crimes.

Using the metric advanced by Levin et al. (2017) and others, what would zero concentration look like? Zero concentration would hold if each crime occurred on a different street segment, as would be required under uniformity. However, a scheme in which crimes are randomized to street segments is unlikely — in fact, very unlikely — to produce the result that all 100 crimes occurred on different street segments (Curiel et al., 2018; Prieto Curiel, 2019). As a result, when this metric is applied to a dataset in which there is zero crime concentration by construction, it will indicate a positive amount of crime concentration. We show this using a simple simulation and later, in Section 5, we present evidence on the degree to which this metric yields an overestimate of crime concentration in empirical data.

3 An Adjusted Measure of Crime Concentration

In this section, we use randomization to propose a simple and easily interpretable way to identify the extent to which crimes are spatially concentrated. [11] We begin with a simple example and lay out our

[11] We note that we are not the first to propose that simulating the random assignment of crimes to street segments is of value in this domain. Indeed both Levin et al. (2017) and Hipp and Kim (2017) utilize simulation to elucidate the

proposed framework. Consider a city that has n street segments and experiences j crimes. In the absence of concentration, what share of street segments *should* account for one quarter or one half of crimes? The rule advanced by (Levin et al., 2017) suggests that we ought to expect uniformity — that is, k percent of street segments account for k percent of crimes. We consider the conditions under which this will be the case by running a simple simulation exercise. Consider a fictional city which has 1,000 street segments and a thought experiment in which the following number of crimes are assigned, at random with replacement, to these 1,000 street segments: 50, 100, 500, 1,000, 5,000, 10,000, 50,000, 100,000 and 1,000,000. What share of crimes would we expect to see represented among the top 25 percent of street segments, ranked according to the number of crimes experienced? Of course, under uniformity, we would expect that 25 percent and 50 percent of street segments to account for 25 percent and 50 percent of the crimes, respectively.

We present the results of the simulation exercise in **Figure 1**. In Figure 1, Panel A plots the share of all street segments and corresponds to the un-adjusted measure of crime concentration as was originally proposed by Weisburd (2015). Panel B plots the share of crime concentration among street segments that actually experience crime, as suggested by Levin et al. (2017) and others. In each panel, we plot the share of street segments accounting for 25 percent of the crimes using the dashed gray line and the share of street segments accounting for 50 percent of the crimes using the dashed black line. Horizontal reference lines are drawn at both 25 and 50 percent along the y-axis and represent the levels of crime concentration at which uniformity is achieved.

In Panel A, we see that when crime density is low relative to the number of street segments (e.g. $j = 50$ crimes amongst 1,000 segments), a very small share, approximately 1.2 percent of street segments, ranked by crime density, account for one quarter of the crimes. Likewise, just 2.4 percent of the street segments account for half of the crimes. As crimes become more common, each measure of crime concentration increases. When the number of crimes is 1,000 equaling the number of street segments, we see that 7.5 percent and 20 percent of street segments account for one quarter and one half of the crimes, respectively. At 10,000 crimes — or 10 crimes per street segment, approximately 15 percent of segments account for one quarter of the crimes and approximately 37 percent of segments account for one half of the crimes. At 1,000,000 crimes — 1,000 per street segment — uniformity is roughly met. As the number of crimes approaches infinity, uniformity will be achieved asymptotically. However, for relatively uncommon crimes or common crimes that are measured

importance of a counterfactual in interpreting crime concentration statistics. However, neither paper utilizes randomization to generate a measure of marginal crime concentration. Recent work by Prieto Curiel (2019) shows, using simulated data, that probabalistic models that use randomization — for instance the "rare event concentration coefficient" (RECC) — outperform common metrics such as entropy and the Gini coefficient in measuring crime concentration.

over a reasonably short window (e.g., one or two years), the asymptotic result will not hold and, as such, an un-adjusted measure of crime concentration will overstate the extent to which crimes are concentrated.

Next, we turn to Panel B which considers the performance of the popular metric which removes crime-free segments. At very low crime densities, this metric performs admirably. Conditioning on non-zero crime street segments leads to near-uniformity at 50 crimes for 1,000 street segments — here, 24.4 percent of the street segments account for one quarter of the crimes and 49 percent of the street segments account for 50 percent of the crimes. Likewise, this metric performs well asymptotically — though, of course, so does the un-adjusted metric. However, the metric performs far less well in the middle of the crime density distribution where we have between 1 and 100 crimes per street segment. For instance, at 1,000 crimes or 1 crime per street segment, we see that 12 percent of the segments account for one quarter of the crimes and 34 percent of the segments account for one half of the crimes. These figures are between one third and one half smaller than uniformity and the result is that crime concentration will be overestimated by between one third and one half. Likewise, at 10,000 crimes or 10 crimes per street segment, we see that 16 percent of segments account for one quarter of the crimes and approximately 39 percent of segments account for one half of the crimes. Incredibly, at these intermediate densities, removing crime-free street segments performs only marginally better than the un-adjusted metric. Since this window (between 1 and 10 crimes per street segment) is an extremely common density among the data that has been studied in the extant literature, the scope for the removal of crime-free segments to overstate crime density is unfortunately quite high.[12]

The thought experiment presented in Figure 1 makes clear that uniformity is an asymptotic result and does not hold in most empirical applications. We further see that removing the zero crime street segments does not substantively correct this issue at most crime densities. We thus propose a "corrected" metric of crime concentration that allows us to quantify the *marginal* degree of crime concentration above and beyond that which would be expected as an artifact of the density of the crime data:

$$mcc_{ij}^{k} = cc_{ij}^{k} - cc_{ij}^{k*} \tag{1}$$

In (1), mcc_{ij}^{k} represents the marginal crime concentration in city i for crime type j and crime share k, where, for our purposes, $k =$ either 25 or 50 percent. cc_{ij}^{k*} is the crime concentration that is actually

[12]In our data which spans between 10 and 15 years in three of the largest cities in the United States, the number of overall crimes per street segment varies between 35 and 115. Individual crime types are far less dense and vary between 0.5 and 10.

experienced in city i (i.e., the measure proposed by Weisburd) for crime type j and cc^k_{ij} is the crime concentration obtained under randomization with replacement. Since each randomized iteration of our randomization procedure will lead to a slightly different result, cc^k_{ij} will, in practice, be the mean crime concentration across a large number of trials.[13] The larger is the value of mcc^k_{ij}, the greater the degree of true crime concentration. Consider, for instance, a crime type for which $cc^{25}_{ij} = 10$ percent and $cc^{25*}_{ij} = 4$ percent. What this means is that, under the randomization of crimes to street segments, we would expect 10 percent of street segments to account for one quarter of the crimes. In reality, only 4 percent of street segments accounted for one quarter of the crimes. Hence, $mcc^{25}_{ij} = 10$ percent - 4 percent = 6 percent. Accordingly, the additional share of street segments needed to account for one quarter of the crimes under randomization is 6 percent. Another way to express this is that crime is 2.5 times more concentrated than under randomization. Critically, unlike the standard crime concentration metric, higher *marginal* crime concentration indicates that crime is more concentrated. In Section 5, we estimate mcc^{25}_{ij} and mcc^{50}_{ij} for a variety of different crime types for each of our three cities: New York City, Chicago and Philadelphia.

4 Data

We derive estimates of the degree of marginal crime concentration using public crime microdata from three of the five largest cities in the United States: New York City (January 1st 2006 - December 31st, 2018), Chicago (January 1st, 2001 - May 4th, 2019) and Philadelphia (January 1st, 2006 - May 11th, 2019).[14, 15] We focus on a relatively long time period in order to better capture the spatial dynamics of crime. We note that, by focusing on a shorter time window — e.g., one year — the problem of non-uniformity will be even larger.

The data correspond to all crimes known to the city's municipal law enforcement agency. Each data set contains the coordinates where each crime occurred, allowing us to determine the street on which the crime happened.[16] The data also provide details on the type of offense, which we use to examine five categories

[13] In theory, the distribution of crime concentration across random iterations can be used to test whether crime concentration is statistically significant. in practice, there is little variation among trials in cc^{k*}_{ij} and, as such, such a test of statistical significance will be very sensitive — perhaps overly sensitive (Hipp and Kim, 2017).

[14] The crime datasets were downloaded from each city's Open Data website. Chicago: https://data.cityofchicago.org/Transportation/Street-Center-Lines/6imu-meau. New York City: https://data.cityofnewyork.us/Public-Safety/NYPD-Complaint-Data-Historic/qgea-i56i/data, https://data.cityofnewyork.us/Public-Safety/NYPD-Complaint-Data-Current-Year-To-Date-/5uac-w243/data. Philadelphia: https://www.opendataphilly.org/dataset/crime-incidents.

[15] We focus on these three cities because crimes from a fourth large city — Los Angeles — are coded primarily to intersections rather than street segments. Likewise, the city of Houston does not provide a shapefile of the city's street segments, excluding that city from the analysis.

[16] Fewer than 1 percent of crimes in each city have missing coordinates. As they could not be matched to a street, these

on crime in addition to total crimes: murder, robbery, assault (simple and aggravated), motor vehicle theft, and larceny/theft. In keeping with prior literature, we assign crimes to street segments by creating a 50-foot buffer around each street segment in the city and checking the location of each crime against these buffers to determine the street segment on which a given crime took place (Ratcliffe, 2012; Lee et al., 2017).[17,18] Crimes that occurred within 50 feet of a single street are considered to have occurred on that street segment. Following Weisburd (2015), we drop any crime that occurs in an intersection (i.e. matches with two or more street segments) or does not match to any street segments. There are substantial differences in the number of crimes geocoded to a single street segment rather than an intersection between each city. For both New York City (71%) and Chicago (94.4%), the majority of crime incidents are located within 50 feet of only one street segment, significantly larger than Philadelphia's 41% due to Philadelphia crimes being more commonly geocoded to a street intersection. To determine which police command each street segment is on, we joined the street segment shapefile with the police district shapefile.[19] Approximately 4 percent of street segments did not match with a police district or were matched with multiple police precinct; these street segments are excluded from the analyses that use police precinct.

We continue our discussion of the data by presenting descriptive statistics on crime in our three cities. **Table 1** presents, for each of our cities, the number of street segments as well as the number of crimes in the complete data set and in 2018, the last full year of data available. The cities included in this study vary widely with respect to the number of street segments in the city, though they are in rough accordance with the city's population. Philadelphia has slightly over 41,000 street segments, Chicago has about 56,000, and New York City has nearly 120,000. Chicago contains the largest number of crimes in our data,

crimes were removed from the data.

[17]The street segment shapefiles were downloaded from each city's Open Data website. While some prior literature edits the shapefiles they used, we did not edit these files in any way and used them exactly as downloaded from each city's website. Chicago: https://data.cityofchicago.org/Transportation/Street-Center-Lines/6imu-meau. New York City: https://data.cityofnewyork.us/City-Government/NYC-Street-Centerline-CSCL-/exjm-f27b. Philadelphia: https://www.opendataphilly.org/dataset/street-centerlines.

[18]Prior to merging each city's coordinates with the street segment shapefile, the crime data was projected to the proper coordinate reference system (CRS) based on the CRS of the given shapefile.To check the accuracy of both the coordinates and the merging process, a small number of coordinates were manually checked to ensure that they were located on the street they were merged to and that the address corresponded with the coordinates provided.The merging was conducted using R statistical software with the package sf.

[19]As with the spatial join of the crime coordinate and street segments, this join was done using *R* statistical software and with the sf package. All police precinct shapefiles were downloaded from their city's Open Data website. Chicago: https://data.cityofchicago.org/Public-Safety/Boundaries-Police-Districts-current-/fthy-xz3r. New York City: https://data.cityofnewyork.us/Public-Safety/Police-Precincts/78dh-3ptz. Philadelphia: https://www.opendataphilly.org/dataset/police-districts.

approximately 6.4 million, a function of the high crime rate in the city, the near complete matching of crime to a single street segment, and the fact that the available data extends as far back as 2001. Philadelphia and New York City have fewer crimes with 1 million and 4.6 million total crimes, respectively. While the total number of crimes differ between cities, the makeup of each city's crime is similar. Larceny in the most common crime in each city, consisting of between 21% (Chicago) and 27% (New York City) of crimes. In each city, murder is rare relative to other crimes, comprising just 0.1% of crimes reported in the city. These trends are roughly similar when examining crime that occurred in 2018, the last full year of data available.

Next, we consider crime concentration in each of our three cities, replicating the canonical figure from Weisburd (2015) which presents cc_{ij}^{25*} and cc_{ij}^{50*} for each of five large cities: Cincinnati OH, New York, NY, Sacramento, CA, Seattle, WA and Tel Aviv-Yafo (Israel). These data are presented in **Figure 2**, Panel A (crime concentration = 25 percent) and B (crime concentration = 50 percent). The gray bars represent the original cities in Weisburd's convenience sample. The black bars represent the three large cities for which we have data. Note that NYC is in both samples — the estimates differ slightly insofar as the sample years are slightly different. In Weisburd's convenience sample, in general, between 1-2 percent of street segments account for 25 percent of the crimes and between 4 and 6 percent of the street segments account for 50 percent of the crime, depending on the city. In our very large cities, crime is a little bit less concentrated but not dramatically so.

Crime is most concentrated in NYC which is relatively safe — 1.2 percent of street segments account for one quarter of the crimes and 4.2 percent of street segments account for one half of the crimes. Crimes are less concentrated in Chicago and Philadelphia which have higher levels of crime. In Chicago 2.8 percent of segments account for one quarter of the crimes and 9.4 percent of the segments account for one half of the crimes. In Philadelphia, those numbers are 2.1 percent and 8.2 percent respectively. Hence, the empirical regularity documented in Weisburd (2015) appears to roughly hold in our sample of cities too. In the next section, we characterize the extent to which crimes are concentrated, relative to what we argue is the ideal counterfactual — that which is generated using randomization with replacement rather than uniformity.

5 Results

5.1 Citywide Crime Concentration

We begin discussion of our findings by comparing the standard (un-adjusted) measure of crime concentration with crime concentration under randomization in each of our three cities. In **Figure 3** we present these results using overall crimes as well as disaggregated crimes of following types: murder, robbery, assault, motor vehicle theft and larceny. Results are presented for each of our three cities and for crime concentration at 25 percent as well as 50 percent. Actual crime concentration is represented by the black bars; crime concentration under randomization is represented by the gray bars. Consistent with computations presented in Weisburd (2015), in NYC, just over 1 percent of street segments account for one quarter of the crimes and just under 5 percent of street segments account for half of the crimes. On the other hand, under randomization, 15 percent of street segments account for one quarter of the crimes and approximately 35 percent of the street segments account for half of crimes. Thus, while crime is substantively concentrated, empirical crime concentration is substantially smaller than that which is implied by the standard measure.

Next, we turn to robberies, a common street crime. Here, we see that the share of street segments that account for one quarter of the robberies in the empirical data — approximately 1 percent — is not dramatically different from the share of street segments in the simulated data — approximately 3 percent. Referring to our suggested computation of marginal crime concentration (mcc_{ij}^{k}), we would subtract cc_{ij}^{k*} (1 percent) from cc_{ij}^{k} (3 percent) to obtain $mcc_{ij}^{k} = 2$ percentage points. In other words, actual crime concentration is just two percentage points smaller than would be expected under random assignment of crimes to street segments. Auto theft, like robbery, is concentrated to a small degree — by approximately 1 percentage point. Assaults and larcenies, on the other hand, are considerably more concentrated — by approximately 8-9 percentage points. Referring to Figures 3B and 3C, the data are substantively similar for both Chicago and Philadelphia.

We next compare our measure of marginal concentration to the measure of crime concentration that is obtained using the method advanced by Levin et al. (2017) which excludes crime-free street segments. Recall that, in Section 2.3 we claimed that this method of removing zero crime segments would yield a measure of crime concentration that is biased upward, a prediction that is supported by the simulations summarized in Figure 1. Here, we present empirical evidence for this claim using data from our three cities. Results are summarized in **Tables 2A and 2B**. These two tables describe concentration at 25 and 50 percent of crimes, respectively and have a parallel structure. The tables report several key crime concentration metrics for each five crime types (murder, robbery, assault, motor vehicle theft and larceny) and aggregate crime in each of our three cities. Each table has five columns. The first column reports the proportion of street segments, when ranked in descending order of crime incidence, that account for k percent of each type of crime. This is the standard (un-adjusted) measure of crime concentration referenced by Weisburd (2015). The second column reports the same quantity, conditioning on non-zero crime segments. The third column reports the same quantity in simulated data in which crimes are randomized to street segments, with replacement. The final two columns use the information in columns (1)-(3), to compute *marginal* crime concentration. Column (4) reports the measure of marginal concentration that we lay out in Section 3, equation (1). Column (5) reports the measure of crime concentration that is implied by the approach suggested by Levin et al. (2017).[20]

We begin our discussion of Table 2A which corresponds with the share of segments that account for one quarter of crimes. Referring to Panel A which uses data from New York City, we see that 1.2 percent of street segments account for one quarter of the crimes in the raw data. Conditioning on segments which experienced at least one crime, one quarter of crimes accrued to the top 2.6 percent of street segments. In simulated data, one quarter of the crimes would accrue to the top 14.8 percent of segments. What does this imply for our measure of marginal crime concentration and for the metric advanced by Levin et al. (2017) that excludes crime-free segments? Using this metric, we see evidence of appreciable crime concentration. Even removing crime-free street segments, a very small share of segments accounted for a disproportionate share of crime. This finding is reflected in their measure of marginal crime concentration of 22.4, indicating that crime concentration is 22.4 percentage points greater than is seen under uniformity —their implicit counterfactual. On the other hand, our measure of crime concentration is 13.7, indicating that crime concentration is 13.7 percentage points smaller than under the counterfactual of random assignment. Our measure of crime concentration is thus 50 percent smaller, a ratio that is consistent with the prediction that we might have made using the simulation exercise summarized in Figure 1.

Next, we turn to murder. In the raw data, 0.1 percent of street segments accounted for 25 percent of the murders in New York City. Conditioning out the crime-free street segments, just over one fifth of the street segments which experienced a murder explain one quarter of the murders. This yields a marginal crime concentration of 3.8 percentage points, using LRD's proposed metric. The implication is that, while murder is not very concentrated, it is to some degree. On the other hand, the share of street segments accounting for one quarter of murders is equal in the empirical and the simulated data implying that murders are not concentrated. Hence, the implication is that murders in NYC are not concentrated at all.[21]

[20] As a reminder, our measure of marginal crime concentration compares the share of street segments that account for k percent of crime in the empirical data (column 1) to the share of street segments that account for k percent of crime in simulated data (column 3), subtracting the former from the latter. The measure of marginal crime concentration implied by Levin et al. (2017) is given by $k - nzcc_{ij}^{k}$ where $nzcc_{ij}^{k}$ is the share of crimes that are accounted for by the top k percent of street segments with at least one crime for city i and crime type j.

[21] Due to the sparsity of murders in the data, caution should be exercised in drawing such a conclusion. The reason for our caution is that when crime data are very sparse, we will be underpowered to detect concentration. To see this, consider a society in which there are 1,000 street segments and 2 crimes. Even if those 2 crimes have an elevated probability

A similar story can be seen for auto theft. Levin et al. (2017) find evidence of appreciable concentration for auto thefts when they condition on the segments that experienced at least one auto theft. However, once we account for the simulated distribution of crimes under randomization, we fail to see evidence of appreciable concentration — auto thefts are concentrated by only one percentage point more than what would occur via randomization. A similar story can likewise be told for robbery which is concentrated but to a considerably smaller degree than is implied by the metric which removes crime-free segments.

Turning to assault and larceny, we see considerable evidence of crime concentration albeit less than has been measured in the prior literature. The measures are quite similar by city, especially for overall crime, thus providing support for the idea that crime concentration may well be highly stable across cities. The same relationship can be found in Table 2A which reports the share of street segments that account for half of the crimes.

5.2 Within-City Crime Concentration

We next address the extent to which crime concentration varies *within a city*, a topic which has received comparatively less attention in the literature. We begin by characterizing the extent to which there is variation in crime concentration among police commands in the same city. This information is presented in **Tables 3A and 3B** which address crime concentration among 25 percent and 50 percent of crimes, respectively. Crime concentration measures are reported separately for each of our three cities. In each table, column (1) reports the average share of street segments in a precinct that cumulatively account for 25 percent of crimes of each type.[22] Column (2) reports the share of street segments that account for 25 percent of crimes under simulation and Column (3) reports marginal crime concentration which is simply equal to Column (2) minus Column (1). In columns (4)-(6) we report standard deviations for each of the three measures.[23]

In drawing inferences from Table 3A, we focus primarily on the variation around the mean level of crime concentration at the precinct-level.[24] We begin by focusing on the standard measure of crime concentration which does not adjust for the random distribution problem in low density data. In our three cities, in an average command, between 2.1 percent (Philadelphia) and 3.8 percent (Chicago) of street segments account for one quarter of the overall crimes. The standard deviations around these means are 1.4 percent,

of occurring on the same dangerous street segment, in most realizations of the data, those crimes will likely end up on different street segments thus implying that crimes are not concentrated.

[22] Note that these computations differ from citywide average since we are not weighting each precinct by its total crime count.

[23] We note that, in each city, one outlier police command is excluded. This includes New York City's Central Park precinct and the police districts covering O'Hare International Airport in Chicago and the Philadelphia International Airport. Each of these precincts contains very few street segments (< 18) and, accordingly, concentration metrics do not behave normally.

[24] Command-level descriptive data for our three cities are available in Appendix tables 1A, 1B and 1C.

3.6 percent and 1 percent in New York City, Chicago and Philadelphia, respectively. While these standard deviations might seem small at first glance, we note that they are large relative to their respective means and, as such, are consistent with a large amount of variability in crime concentration within a city.

Next, we consider our measure of marginal crime concentration which is robust to the measurement issues discussed in Sections 2.2 and 2.3. Marginal crime concentration is high for overall crime as well as assault and larceny, is intermediate for robbery and auto theft and is nearly zero for murder — though we urge caution in interpreting estimated crime concentration for murder. There is likewise considerable variability around this measure within a city. In New York City, marginal crime concentration varies from a low of 13.7 in the 111th precinct in the Bayside section of Queens, one of the safest neighborhoods in the city, to a high of 22.5 in 14th precinct which covers the southern portion of Midtown Manhattan which includes Times Square. This is perhaps intuitive. In both neighborhoods, crimes are highly concentrated — the share of street segments that account for one quarter of the crimes is 1.3 in Midtown Manhattan and 2.1 in Bayside. However, in Bayside, a quiet residential neighborhood, there are relatively few crimes per street segment (28,924 over 3,850 street segments) whereas in Midtown South there are many more crimes (108,402) than streets (235), reflecting the fact that this small area experiences a very large amount of human activity. While crime appears to be concentrated in both areas, once differing crime densities are accounted for, we can see that crime is, in fact, far more concentrated in Midtown Manhattan than it is in Bayside. Table 3B presents the same information for the share of street segments that account for 50 percent of the crimes.

The anecdote presented above in which crime concentration in Bayside, Queens is contrasted with that of Midtown South raises a broader question: whether marginal crime concentration varies according to the underlying density of crime in a neighborhood. We have already seen that, for the raw measure of crime concentration this will be true. But is it also true for our corrected measure? We explore this relationship in **Figures 4A and 4B**, where marginal crime concentration is plotted on the y-axis and the number of crimes per street segment is plotted on the x-axis. In these figures we pool all 120 precincts across our three cities though we residualize out the city fixed effects in order to guard against confounding due to between-city differences in crime concentration.

In Figure 4A where we plot marginal crime concentration for 25 percent of crimes, each data point represents a precinct and a quadratic best fit line is drawn through the data. The small number of observations means that the highest-crime communities are highly leveraged and therefore that the slope of the curves drawn through the data are sensitive to outliers. As a result, we urge caution in interpretation. We begin by considering the relationship between marginal crime concentration and crime density for overall crime. At lower crime densities, the slope of the best fit curve is relatively flat, but the slope becomes negative at higher densities indicating that the highest-crime communities experiences lower levels of crime concentration. This relationship is different, however, for several serious street crimes. Robbery becomes *more* concentrated in higher-crime neighborhoods whereas assault is most concentrated towards the middle of the density distribution.

We next consider crime concentration for 50 percent of the crimes in Figure 4B. Here, the relationship between crime concentration and crime density is far more uniform. With the partial exception of robbery and murder (which is not concentrated at all), crime is concentrated to a far lesser degree in the highest crime communities. The contrast between the relationships presented in Figures 4A and 4B is interesting and merits further consideration. When we consider hot sports writ large — the street segments that account for half of the crimes — we see strong evidence that it takes considerably more of these hot spots to account for half the crimes in high-crime communities than in low-crime communities. However, when we focus on only the "hottest" of the hot spots, this is less true. One conclusion that rationalizes the data is that every community has a small number of areas in which crimes are strongly concentrated but that high-crime communities have a longer tail of less pervasive hot spots. The result is that it is, in general, more difficult to target resources in the highest crime parts of a city.[25]

6 Conclusion

In this paper, we build upon recent methodological advances in the measurement of crime concentration and propose a method of measuring crime concentration that is simple, easy to interpret and is robust to a key statistical artifact — caused by sparse crime data — that the recent literature has been working to address. A common solution to this problem which has been advanced by Levin et al. (2017) among others is to measure crime concentration *among street segments that actually experience crime*. We note that while this approach will correct some of the upward bias in the measurement of crime concentration, appreciable bias will remain in most empirical applications.

Our proposed solution — comparing the actual distribution of crimes to a distribution of crimes under

[25] OBrien (2019) notes that, to an extent, a negative relationship between crime concentration and crime density might be a statistical artifact.

the randomization with replacement — allows us to generate a corrected measure of crime concentration that is robust to problems posed by sparse crime data. Our approach compliments recent advances which render Gini coefficient-based metrics robust to the same problem (Bernasco and Steenbeek, 2017; OBrien, 2019; Mohler et al., 2019).[26] While the Gini coefficient allows researchers to characterize crime concentration without appealing to arbitrary cutoffs (e.g., 25 or 50 percent of crimes), a virtue of our approach is that it preserves the simplicity and interpretability of Weisburd's original crime concentration metric. Our proposed metric — marginal crime concentration — is simply the excess share of crimes that occur in the top k percent of locations. Using this metric, it is easy to compare observed crime concentration to random chance in an intuitive way — for instance, we might say that crime is 2-3 times more concentrated than it would be by chance. In this way, it is similar to positive predictive value (i.e., "precision"), a mainstay of prediction research in the social and computational sciences. Just as comparing the positive predictive value for a high-risk group to baseline risk in a population, we can compare crime concentration in actual versus simulated data in order to generate a metric that is simple and intuitive to understand.[27]

Like our predecessors we find considerable evidence that crimes are concentrated among the cities we study and, accordingly, we provide additional support for the law of crime concentration. However, the extent to which the law of crime concentration applies requires some qualification. In this research, we note that in three of the largest cities in the United States, while crime is highly concentrated in the aggregate, murders are effectively unconcentrated and the robberies and auto thefts are only concentrated to a very small degree. On the other hand, assaults and larcenies exhibit fairly substantial concentration at the city level. These results are qualitatively different than a number of those in the literature.

We also extend this analysis to the study of crime concentration *within police commands*. We find that while city-level concentration is remarkably stable across our three cities, the extent to which crimes are concentrated within our cities varies considerably. Accordingly, the law of crime concentration cannot be said to hold at lower levels of aggregation. We furthermore document evidence that crime tends to be less concentrated in higher-crime communities, indicating that crimes are less concentrated in precisely the communities in which efficient resource allocation is needed the most.

[26] A conceptually similar approach — that of the rare event concentration coefficient — has been shown by Prieto Curiel (2019) to outperform the modified Gini coefficient in measuring crime concentration using simulated data.

[27] We further note that this methodology also has broad applicability to other domains in criminological research — for example to cohort studies of young people which invariably show that a small share of the population is responsible for an outsize share of the crimes and to "early warning systems" that police departments use to identify potentially problematic police officers and which are based on the premise that a small share of police officers are responsible for a disproportionate share of misconduct.

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Table 1: Summary Statistics

	New York City	Chicago	Philadelphia
Time period	Jan 2006 - Dec 2018	Jan 2001 - May, 2019	Jan 2006 - May, 2019
Number of Street Segments	119,467	56,338	41,009
Percentage of Crime at Intersections	25.8%	5.4%	59%
Crime During Entire Studied Period			
All crimes	4,585,280	6,419,106	1,051,840
Murder	4,207	9,386	1,762
Robbery	131,492	237,517	29,037
Assault	684,394	1,593,989	222,651
Auto theft	82,196	296,561	21,156
Larceny	1,225,234	1,322,269	232,866
Crime During 2018			
All crimes	334,534	251,530	71,078
Murder	243	568	132
Robbery	8,412	9,163	1,684
Assault	55,667	67,385	16,499
Auto theft	3,953	9,559	1,082
Larceny	100,534	60,069	17,885

Note: Table presents descriptive
data on the number of street segments and crimes in each of our three cities: New York City, Chicago and Philadelphia.

Table 2A: Marginal Crime Concentration at 25 Percent of Street Segments

	Share of Segments, Unadjusted (Weisburd)	Share of Segments, Non-Zero Crime Segments	Share of Segments, Simulated	Marginal Crime Concentration: Our proposed method	Marginal Crime Concentration: Levin-Rosenfeld-Deckard
A. New York City					
All crimes	1.2	2.6	14.8	13.7	22.4
Murder	.1	21.2	.1	0	3.8
Robbery	.8	8.1	2.9	2.1	16.9
Assault	.9	4	7.3	6.4	21
Auto theft	1.1	12.8	2.1	1	12.2
Larceny	.4	1.4	9.7	9.2	23.6
B. Chicago					
All crimes	2.7	3.8	18.3	15.6	21.2
Murder	.4	18.3	.6	.2	6.7
Robbery	1.8	6.2	6.3	4.5	18.8
Assault	2.2	4.1	13.5	11.3	20.9
Auto theft	3.1	8.5	7	3.9	16.5
Larceny	1.2	2.2	12.7	11.5	22.8
C. Philadelphia					
All crimes	2.1	3.2	16.8	14.6	21.8
Murder	.3	18	.4	.1	7
Robbery	.9	6	3.4	2.5	19
Assault	1.9	4.6	10.9	9	20.4
Auto theft	1.4	9.9	3.1	1.7	15.1
Larceny	.6	1.3	11.1	10.5	23.8

Note: This table reports the share of street segments that account for 25 and 50 percent of each of six crime types: total crime, murder, robbery, assault, auto theft and larceny and three cities: NYC (Panel A), Chicago (Panel B) and Philadelphia (Panel C). Column (1) reports crime concentration for all street segments, Column (2) reports crime concentration for street segments with non-zero crime and Column (3) reports simulated crime concentration arising generated by randomizing crimes to street segments, with replacement. The final two columns report *marginal* crime concentration using both our proposed method and by the method proposed by Levin-Rosenfeld-Deckard.

Table 2B: Marginal Crime Concentration at 50 Percent of Street Segments

	Share of Segments, Unadjusted (Weisburd)	Share of Segments, Non-Zero Crime Segments	Share of Segments, Simulated	Marginal Crime Concentration: Our proposed method	Marginal Crime Concentration: Levin-Rosenfeld-Deckard
A. New York City					
All crimes	4.5	9.9	34.7	30.1	40.1
Murder	.3	47.5	.3	0	2.5
Robbery	2.5	25.4	7.2	4.6	24.6
Assault	3.2	13.7	18.4	15.2	36.3
Auto theft	3.3	37.9	4.8	1.5	12.1
Larceny	2.8	8.7	23.7	20.9	41.3
B. Chicago					
All crimes	9.2	12.6	40.5	31.3	37.4
Murder	1	45.6	1.2	.2	4.4
Robbery	5.9	20.8	15.2	9.4	29.2
Assault	6.9	13	32.2	25.3	37
Auto theft	8.9	24.1	16.7	7.9	25.9
Larceny	6.6	11.8	30.6	24	38.2
C. Philadelphia					
All crimes	8.2	12.6	37.9	29.6	37.3
Murder	.7	45.4	.8	.1	4.6
Robbery	3.6	22.8	10.3	6.7	27.2
Assault	6.5	15.5	26.7	20.2	34.5
Auto theft	4.2	29.1	8.2	4	20.9
Larceny	4.8	10.2	27.1	22.4	39.8

Note: This table reports the share of street segments that account for 25 and 50 percent of each of six crime types: total crime, murder, robbery, assault, auto theft and larceny and three cities: NYC (Panel A), Chicago (Panel B) and Philadelphia (Panel C). Column (1) reports crime concentration for all street segments, Column (2) reports crime concentration for street segments with non-zero crime and Column (3) reports simulated crime concentration arising generated by randomizing crimes to street segments, with replacement. The final two columns report *marginal* crime concentration using both our proposed method and the method proposed by Levin-Rosenfeld-Deckard.

Table 3A: Descriptive Statistics: Marginal Crime Concentration by Precinct
25 percent concentration

	Mean			Standard Deviation		
	Share of Segments, Unadjusted	Share of Segments, Simulated	Marginal Crime Concentration	Share of Segments, Unadjusted	Share of Segments, Simulated	Marginal Crime Concentration
			A. New York City			
All crimes	2.6	20.6	18	1.4	1.7	1.7
Murder	.6	1.2	.6	.5	.9	.5
Robbery	2.2	9	6.9	1.3	3.7	2.7
Assault	2	15	13	1.1	3.3	2.8
Auto theft	2.9	7	4.1	1.3	2.1	1.2
Larceny	1.7	17	15.3	1.3	2.9	2.8
			B. Chicago			
All crimes	3.8	22.2	18.5	3.6	.7	3.1
Murder	1.5	2.8	1.4	1.7	1.6	.6
Robbery	2.6	13.5	11	2.3	2.5	1.5
Assault	3.1	19.6	16.6	3.1	1.4	2.1
Auto theft	5	14.5	9.5	4.3	1.7	3
Larceny	1.5	19.2	17.7	1.9	1.2	1.3
			C. Philadelphia			
All crimes	2.1	19.3	17.2	1	.8	.6
Murder	.5	1	.5	.4	.5	.2
Robbery	1	6.3	5.2	.5	1.5	1.1
Assault	2	14.1	12.2	1.2	1.6	.9
Auto theft	1.8	5.2	3.3	1.4	1.5	.7
Larceny	.6	14.5	13.9	.5	1.1	.8

Note: This table reports the precinct-level mean and standard deviation of street segments that account for 25 and 50 percent of each of six crime types: total crime, murder, robbery, assault, auto theft and larceny and three cities: NYC (Panel A), Chicago (Panel B) and Philadelphia (Panel C). Columns (1)-(3) report means; Columns (4)-(6) report standard deviations. Column (1) reports the mean share of street segments that account for 50 percent of the crimes in a precinct, Column (2) reports the mean simulated share of street segments that account for 50 percent of crimes in a precinct, generated by randomizing crimes to street segments with replacement and Column (3) reports marginal crime concentration which is equal to Column (2) minus Column (1). Columns (4)-(6) report the standard deviation for each of these three statistics. Note that, in each city, one outlier police district is excluded. This includes the Central Park precinct in NYC, and the police districts covering O'Hare International Airport in Chicago and the Philadelphia International Airport.

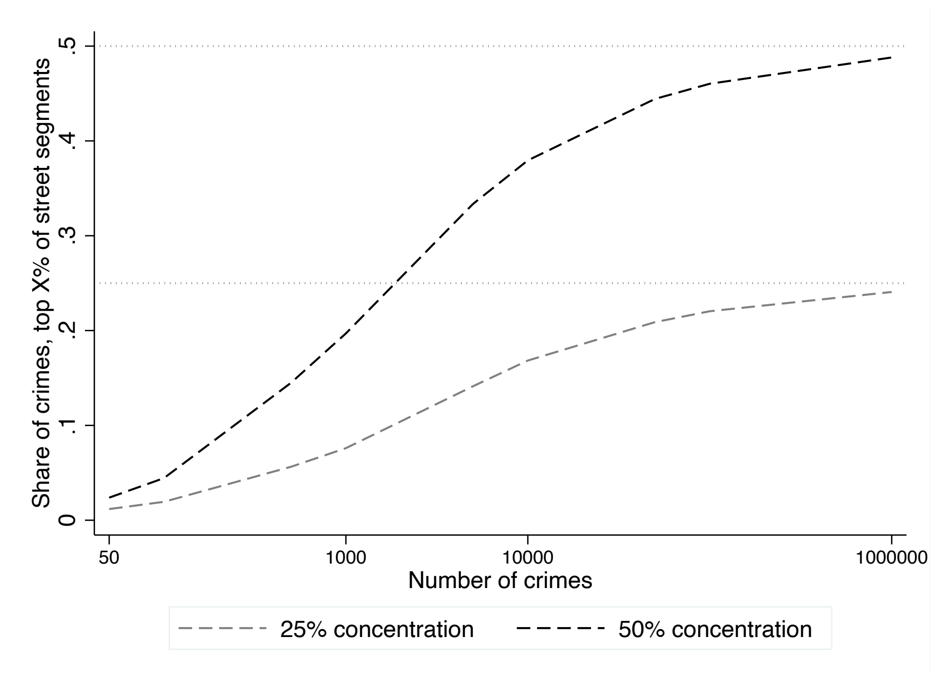
Table 3B: Descriptive Statistics: Marginal Crime Concentration by Precinct
50 percent concentration

	Mean			Standard Deviation		
	Share of Segments, Unadjusted	Share of Segments, Simulated	Marginal Crime Concentration	Share of Segments, Unadjusted	Share of Segments, Simulated	Marginal Crime Concentration
A. New York City						
All crimes	9.3	43.8	34.5	9.6	2.6	7.7
Murder	1.3	2.6	1.2	1.3	2.3	1.2
Robbery	7	22.1	15.1	7.3	8.2	4
Assault	6.3	34.3	28	6.6	6.3	4.1
Auto theft	8.7	17.5	8.8	6	4.9	2.3
Larceny	6.6	38	31.4	10.2	5.1	7.8
B. Chicago						
All crimes	11.9	46.3	34.5	8.6	1	7.8
Murder	4	7.2	3.2	3.9	4.4	1.2
Robbery	9.1	31.9	22.7	6.9	5.1	4
Assault	9.3	42.4	33.1	8.3	2.2	6.6
Auto theft	13.7	33.8	20.1	8.7	3.2	6
Larceny	8.7	41.9	33.1	6.2	2	4.5
C. Philadelphia						
All crimes	8.1	42	33.8	3.8	1.2	2.7
Murder	1.5	2	.5	.9	1.2	.4
Robbery	4.4	16	11.6	2.2	3.6	1.7
Assault	6.7	33.1	26.3	3.7	3.1	1.3
Auto theft	5.6	13.6	7.9	3.4	3	1.3
Larceny	5.2	33.9	28.7	2.5	2	1.4

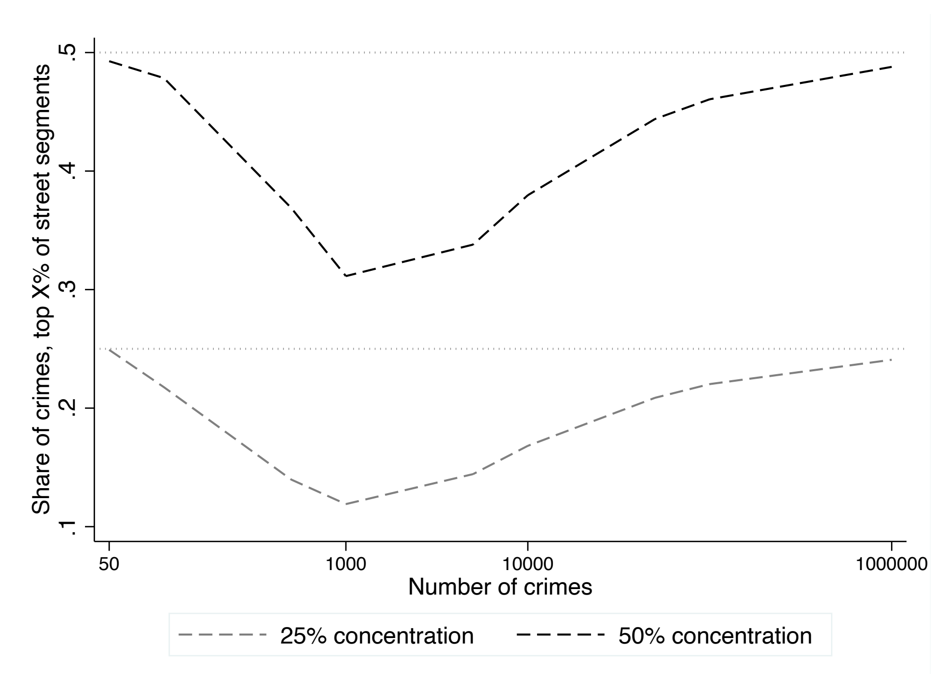
Note: This table reports the precinct-level mean and standard deviation of street segments that account for 25 and 50 percent of each of six crime types: total crime, murder, robbery, assault, auto theft and larceny and three cities: NYC (Panel A), Chicago (Panel B) and Philadelphia (Panel C). Columns (1)-(3) report means; Columns (4)-(6) report standard deviations. Column (1) reports the mean share of street segments that account for 50 percent of the crimes in a precinct, Column (2) reports the mean simulated share of street segments that account for 50 percent of crimes in a precinct, generated by randomizing crimes to street segments with replacement and Column (3) reports marginal crime concentration which is equal to Column (2) minus Column (1). Columns (4)-(6) report the standard deviation for each of these three statistics. Note that, in each city, one outlier police district is excluded. This includes the Central Park precinct in NYC, and the police districts covering O'Hare International Airport in Chicago and the Philadelphia International Airport.

Figure 1: Crime Concentration, Simulated Data for n = 1,000 street segments

Panel A: Unadjusted crime concentration, all street segments



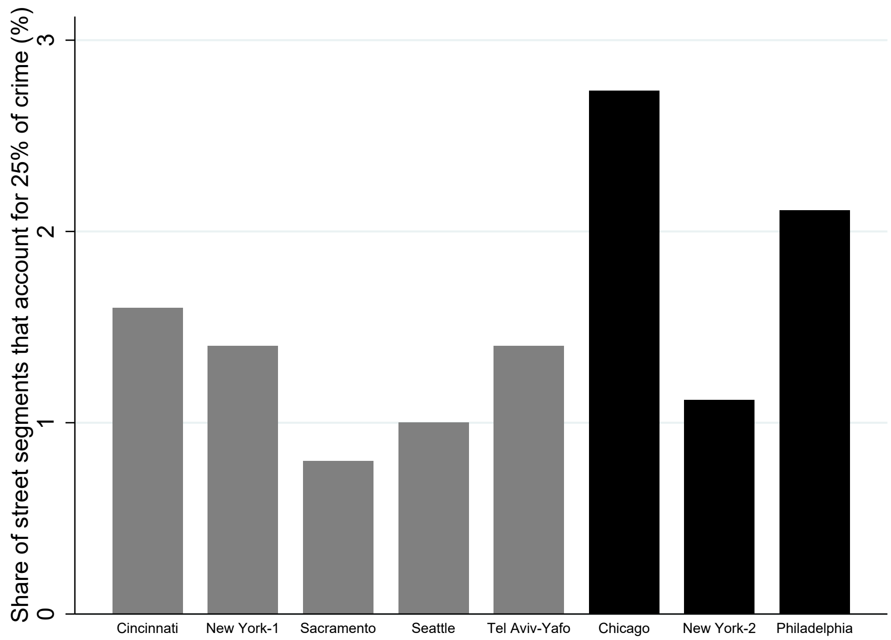
Panel B: Unadjusted crime concentration, non-zero crime street segments



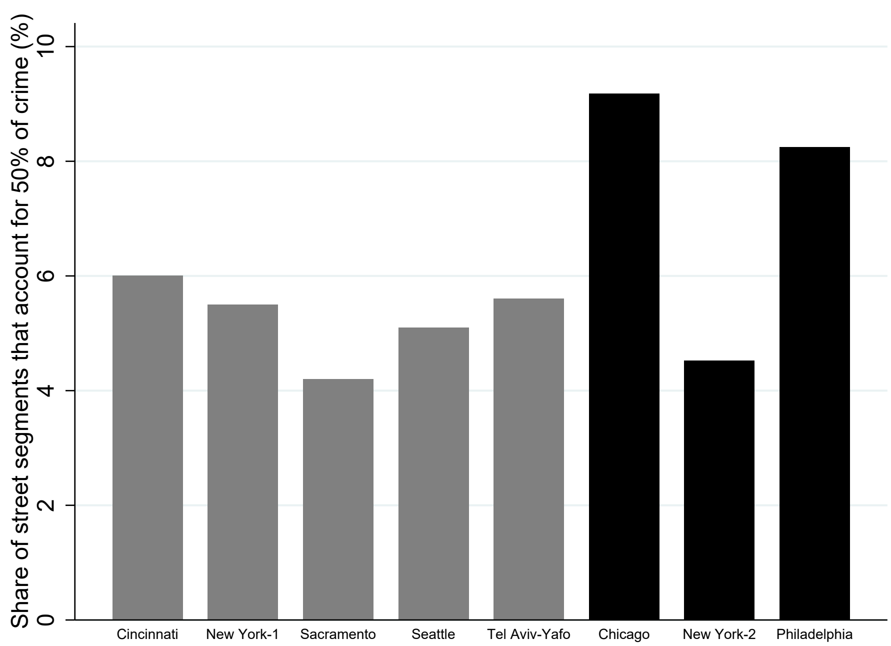
Note: Figures plot the share of street segments that account for 25 percent (Panel A) and 50 percent (Panel B) of crimes, in simulated data in which crimes are randomly assigned to street segments, with replacement. The number of street segments is fixed at 1,000 while the number of crimes is allowed to very along the x-axis. The x-axis has been transformed using a logarithmic scale.

Figure 2: Share of Crimes Among the Top 25 and 50 Percent of Street Segments, by City

Panel A: Unadjusted crime concentration, all street segments

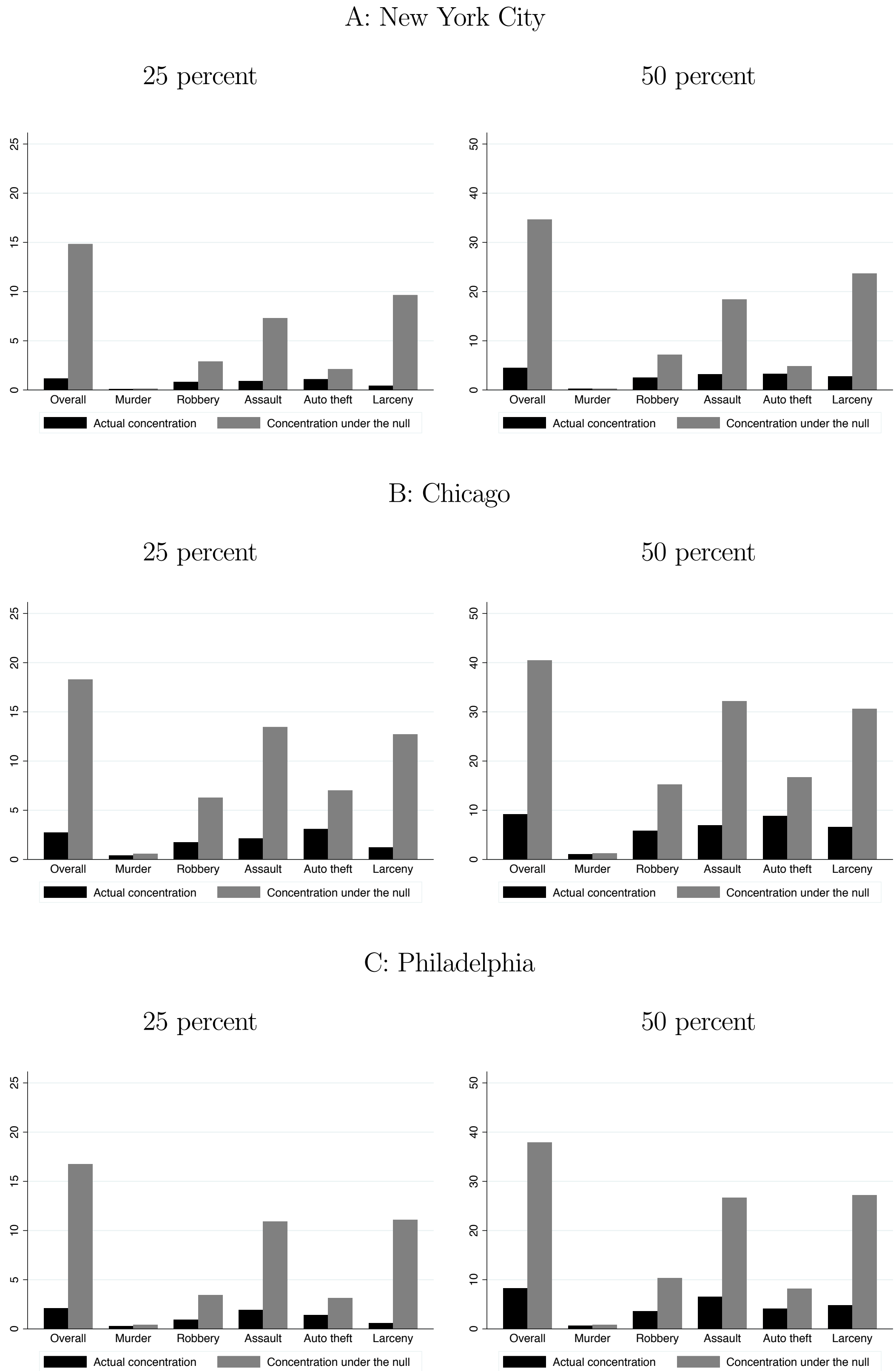


Panel B: Unadjusted crime concentration, non-zero crime street segments



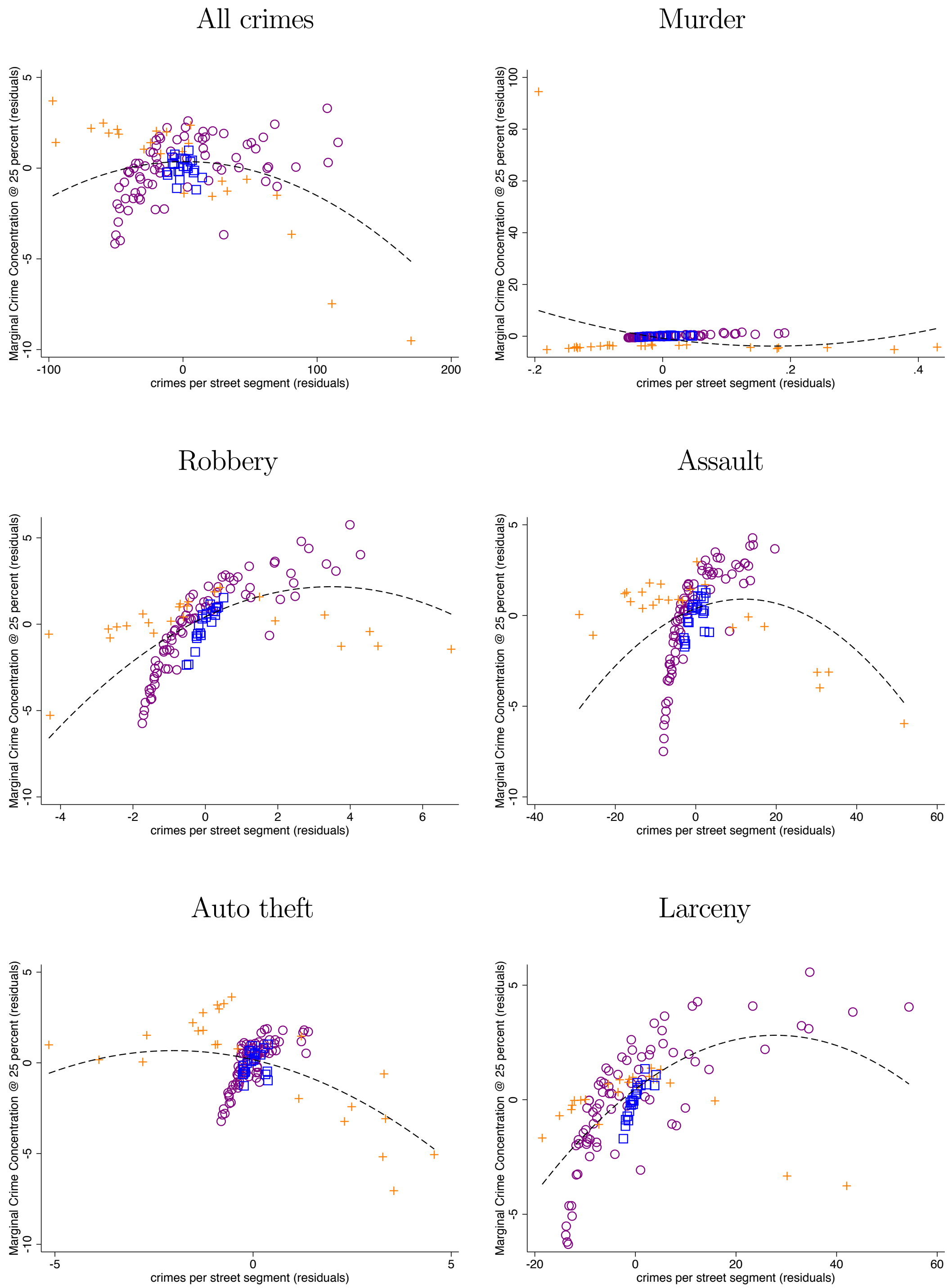
Note: Figures plot the share of street segments that account for 25 percent (Panel A) and 50 percent (Panel B) of crimes. The gray bars are replicated from Table 3 in Weisburd (2015). The black bars correspond to data from New York City, Chicago and Philadelphia (our sample).

Figure 3: Actual vs. Simulated Share of Street Segments Accounting for K Percent of Crimes



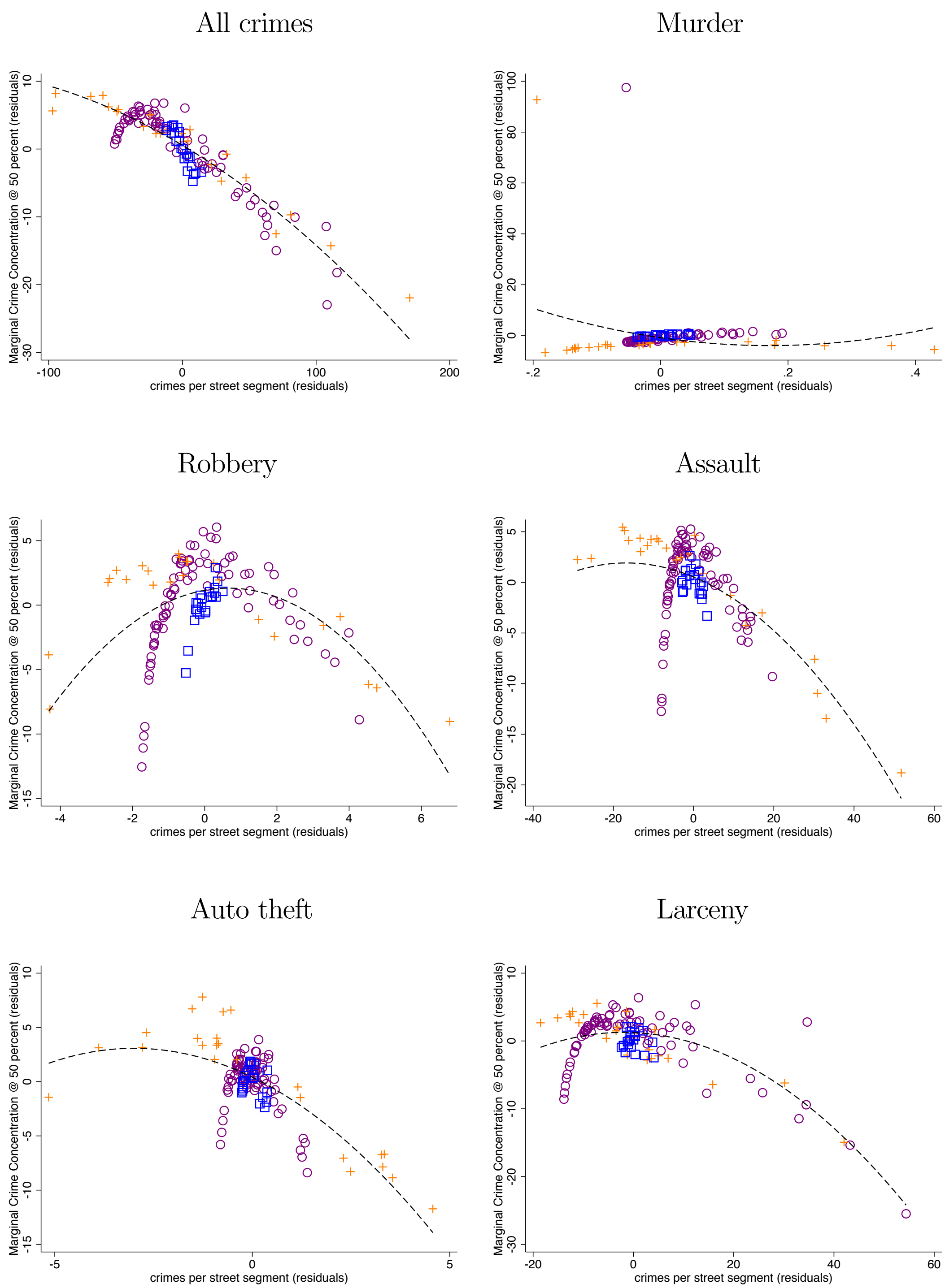
Note: Figures plot the share of street segments that account for 25 percent and 50 percent of crimes. The black bars represent the actual data the gray bars represent simulated data in which crimes are randomized to street segments, with replacement. Crimes are concentrated when the heights of the two bars are different.

Figure 4A: Marginal Crime Concentration by Precinct, Street Segments Accounting for 25 Percent of Crimes



Note: Figures plot marginal crime concentration for 25 percent of crimes on the y-axis against the number of crimes per street segment in each police precinct on the x-axis. Both marginal crime concentration and crimes per street segment have been residualized, removing the city fixed effects. The circular markers plot data for precincts in New York City, the plus markers plot data for precincts in Chicago and the square markers plot data for precincts in Philadelphia. A quadratic best fit curve is drawn through the data points. A positive (negative) relationship in the data means that police precincts with more crimes per street segment experience greater (less) crime concentration.

Figure 4B: Marginal Crime Concentration by Precinct, Street Segments Accounting for 50 Percent of Crimes



Note: Figures plot marginal crime concentration for 50 percent of crimes on the y-axis against the number of crimes per street segment in each police precinct on the x-axis. Both marginal crime concentration and crimes per street segment have been residualized, removing the city fixed effects. The circular markers plot data for precincts in New York City, the plus markers plot data for precincts in Chicago and the square markers plot data for precincts in Philadelphia. A quadratic best fit curve is drawn through the data points to approximate the data generating process.

Appendix Table 1A: Precinct-Level Descriptive Statistics, New York City

District	Number of segments	Crimes	Crimes per segment	Crime, Concentration, 25 percent: Share of segments, Unadjusted	Crime, Concentration, 25 percent: Marginal Crime Concentration	Crime Concentration, 50 percent: Share of segments Unadjusted	Crime Concentration, 50 percent: Marginal Crime Concentration
District 14	235	108402	461.3	1.3	22.5	47.2	1.2
District 18	440	76537	173.9	3.6	19.2	30.5	16.7
District 23	369	64156	173.9	3.5	19.3	30.1	17
District 9	371	61763	166.5	4.6	18.2	34.8	12.3
District 28	240	39793	165.8	1.7	21.2	23.3	23.8
District 24	324	46150	142.4	4.6	18	21.6	25.2
District 81	429	55094	128.4	5.6	16.9	26.3	20.3
District 32	427	54094	126.7	2.1	20.3	19.7	26.9
District 79	570	69520	122	4.4	18	22.5	24
District 77	518	62684	121	4.4	17.9	21.2	25.2
District 71	505	60575	120	5.2	17.2	24	22.5
District 13	551	65094	118.1	2.7	19.6	20.5	25.9
District 30	327	36781	112.5	3.4	19	18.6	27.8
District 46	875	95536	109.2	2.9	19.3	19.3	26.9
District 73	816	86712	106.3	2.9	19.2	16.7	29.5
District 20	381	38067	99.9	4.2	17.9	17.3	28.8
District 42	675	66090	97.9	3.6	18.5	17.8	28.3
District 26	320	28369	88.7	2.2	19.8	11.6	34.4
District 83	666	59034	88.6	7.7	14.2	11.6	34.3
District 6	488	42436	87	4.1	17.8	13.3	32.5
District 48	870	72824	83.7	3.8	18	13.9	31.8
District 40	1307	105097	80.4	1.8	20	12.6	33.1
District 34	625	48330	77.3	4.5	17.2	13.1	32.5
District 44	1318	98616	74.8	2	19.6	13.1	32.3
District 19	897	67060	74.8	3	18.6	10.4	35.1
District 70	967	70921	73.3	2.6	19	8.7	36.7
District 41	839	61490	73.3	1.7	19.9	12.6	32.8
District 52	1122	81710	72.8	2	19.5	11.9	33.5
District 7	561	39269	70	2	19.6	12.1	33.2
District 5	736	45636	62	.8	20.5	8.6	36.5
District 17	513	31609	61.6	4.5	16.9	10.7	34.3
District 67	1380	84378	61.1	2.8	18.4	7.4	37.6
District 78	626	37643	60.1	1.1	20.2	3.7	41.3
District 43	2023	119736	59.2	1.5	19.7	9.1	35.8
District 10	552	29741	53.9	1.6	19.5	10	34.7
District 75	2488	128292	51.6	2.4	18.5	6	38.5
District 33	777	38180	49.1	2.1	18.8	8.9	35.6
District 25	1130	52431	46.4	.6	20.1	6.3	38
District 90	1287	59288	46.1	3	17.7	6	38.3
District 62	1301	57640	44.3	5	15.7	2.1	42
District 60	1225	50715	41.4	1	19.6	4.9	39
District 47	1986	81834	41.2	2.9	17.7	4.5	39.4
District 88	725	29667	40.9	2.6	17.9	5.4	38.5
District 84	1027	41688	40.6	.9	19.7	5.7	38.2
District 49	1585	61988	39.1	2.3	18.1	4.5	39.2
District 103	1724	66101	38.3	1.9	18.5	3.4	40.3
District 1	1304	49910	38.3	.9	19.5	5.1	38.6
District 66	1188	44712	37.6	4.7	15.6	1.6	42
District 69	1200	44565	37.1	2.5	17.8	2.8	40.8
District 101	1125	40625	36.1	1.5	18.8	4.2	39.3
District 115	1604	56844	35.4	3.2	17	2.9	40.5
District 114	2524	85444	33.9	1.3	18.8	2.9	40.3
District 94	978	31470	32.2	3	17.1	2	41.1
District 76	829	24851	30	1.8	18	3.6	39.3
District 72	1418	38656	27.3	3	16.6	2.2	40.3
District 68	1705	45362	26.6	2.2	17.3	1.5	40.9
District 102	2050	54042	26.4	3.4	16.2	.9	41.4
District 61	2145	55772	26	2	17.4	1.6	40.7
District 50	1443	36672	25.4	1.3	18.2	3.2	39.1
District 106	2359	59493	25.2	3.1	16.3	.6	41.6
District 110	2358	54430	23.1	1	18.2	1.5	40.4
District 63	1891	42806	22.6	2.6	16.5	1.1	40.7
District 120	3443	74371	21.6	1.1	17.9	1.6	40
District 104	3011	63739	21.2	2.7	16.2	.8	40.8
District 109	4235	78190	18.5	.9	17.7	1.3	39.7
District 45	2889	52610	18.2	.9	17.7	1.4	39.4
District 113	3523	61188	17.4	2.9	15.6	.5	40.1
District 121	3677	63450	17.3	.7	17.7	.8	39.8
District 108	2639	40593	15.4	1.9	16.2	.5	39.6
District 112	1821	26466	14.5	.8	17.1	.8	39
District 105	5610	64020	11.4	3.2	13.9	.1	38.5
District 107	3160	34875	11	1.4	15.7	.5	38
District 122	5165	51475	10	1.8	14.9	.3	37.5
District 100	2232	20468	9.2	.6	15.9	.8	36.6
District 123	3958	32501	8.2	1.9	14.2	.2	36.6
District 111	3850	28924	7.5	2	13.7	.2	36

Appendix Table 1B: Precinct-Level Descriptive Statistics, Chicago

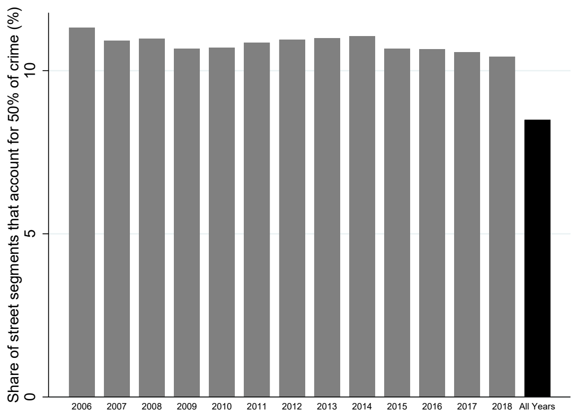
				Crime, Concentration, 25 percent		Crime Concentration, 50 percent	
District	Number of segments	Crimes	Crimes per segment	Share of segments, Unadjusted	Marginal Crime Concentration	Share of segments Unadjusted	Marginal Crime Concentration
District 15	874	262690	300.6	14.2	9.1	35	12.8
District 11	1587	383392	241.6	11.9	11.1	27	20.4
District 3	1457	308214	211.5	8	15	22.3	25
District 7	1864	373899	200.6	5.7	17.1	25	22.2
District 6	2003	356789	178.1	4.7	18	16.6	30.5
District 18	1645	269004	163.5	5.3	17.4	12.9	34
District 10	1699	271246	159.7	4.7	17.9	16.9	30
District 2	1890	287900	152.3	5.5	17.1	14.4	32.4
District 25	2573	350481	136.2	1.4	21	9.1	37.5
District 24	1345	181181	134.7	2.5	20	10.7	35.9
District 1	1784	234183	131.3	5.2	17.2	10.7	35.9
District 19	2151	279734	130	2.8	19.5	9.5	37
District 14	2013	238218	118.3	1.6	20.6	8.7	37.6
District 5	2534	280563	110.7	1.5	20.7	9.2	37
District 20	946	100591	106.3	2.1	20	6.4	39.8
District 4	3626	367792	101.4	2.4	19.7	8.1	38
District 8	5021	415050	82.7	1.2	20.5	5.1	40.5
District 9	3763	307101	81.6	1	20.8	5.4	40.2
District 12	3726	280139	75.2	1	20.6	4.5	40.9
District 17	2481	176429	71.1	.4	21.1	2.7	42.6
District 22	3279	203417	62	.5	20.8	2.5	42.5
District 16	5250	187423	35.7	.2	20	.5	42.9

Appendix Table 1C: Precinct-Level Descriptive Statistics, Philadelphia

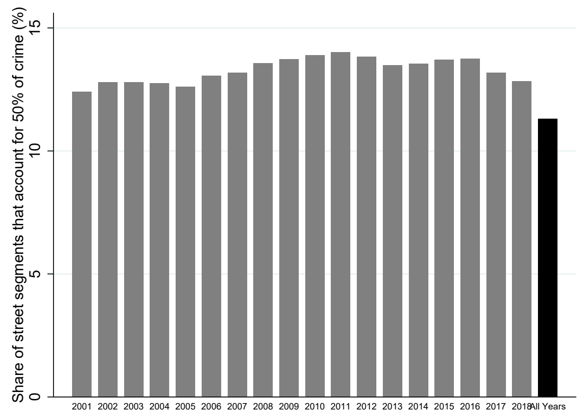
				Crime, Concentration, 25 percent		Crime Concentration, 50 percent	
District	Number of segments	Crimes	Crimes per segment	Share of segments, Unadjusted	Marginal Crime Concentration	Share of segments Unadjusted	Marginal Crime Concentration
District 18	1380	54664	39.6	3.8	16.7	13.3	30.4
District 24	1817	63957	35.2	4.2	16	13.1	30.3
District 12	1952	66080	33.9	3	17.1	13.1	30.1
District 25	1782	59082	33.2	3.1	17	14.1	29.1
District 19	1753	56428	32.2	2.3	17.6	11.8	31.3
District 2	2152	66472	30.9	2.3	17.6	10.2	32.8
District 35	2103	62306	29.6	1.6	18.2	10.3	32.5
District 22	2164	62968	29.1	2.5	17.2	12.1	30.6
District 15	3384	95825	28.3	2.4	17.3	9.5	33.1
District 39	1694	45297	26.7	1.9	17.7	10	32.4
District 14	2696	65731	24.4	1.6	17.8	8.1	33.9
District 9	1294	29664	22.9	2.6	16.6	5.5	36.4
District 16	1190	27209	22.9	2.2	17	6.9	34.9
District 8	2201	47964	21.8	2	17	4.6	37
District 6	1603	33111	20.7	2.8	16.1	6.4	35
District 17	1413	27207	19.3	.8	18	4.9	36.2
District 3	2745	51235	18.7	1.2	17.4	3.6	37.4
District 26	2122	37181	17.5	1	17.5	3.4	37.2
District 1	1189	20365	17.1	.6	17.8	4.4	36.2
District 5	1261	17473	13.9	.9	16.8	2.5	37.1
District 7	1994	26213	13.1	.6	17	2.8	36.6

Appendix Figure
1: Annual and Total Share of Non-Zero Crime Street Segments Accounting for 50 Percent of Crimes

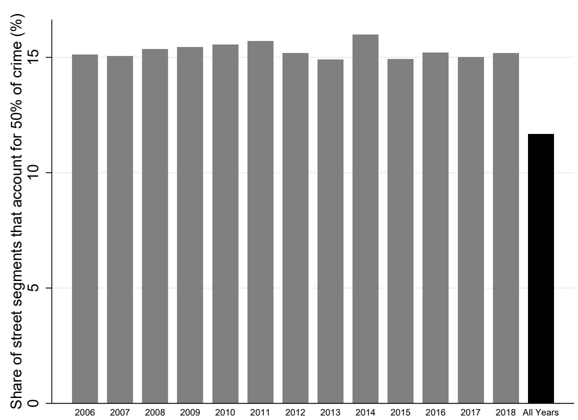
New York



Chicago



Philadelphia



Note: Figures plot the share of non-zero crime street segments that account for 50 percent of total crimes in each city. The gray bars show the share of street segments for each year of data, the black bar shows the share when all years are combined.