Measuring Crime Concentration across Cities of Varying Sizes: Complications Based on the Spatial and Temporal Scale Employed

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Abstract

Objectives: We argue that assessing the level of crime concentration across cities has four challenges: 1) how much variability should we expect to observe; 2) whether concentration should be measured across different types of macro units of different sizes; 3) a statistical challenge for measuring crime concentration; 4) the temporal assumption employed when measuring high crime locations.

Methods: We use data for 42 cities in southern California with at least 40,000 population to assess the level of crime concentration in them for five different Part 1 crimes and total Part 1 crimes over 2005-12. We demonstrate that the traditional measure of crime concentration is confounded by crimes that spatially locate due to random chance. We also use two measures employing different temporal assumptions: a *historically adjusted crime concentration* measure, and a *temporally adjusted crime concentration* measure (a novel approximate solution that is simple for researchers to implement).

Results: There is much variability in crime concentration over cities in the top 5% of street segments. The standard deviation across cities over years for the temporally adjusted crime concentration measure is between 10% and 20% across crime types (with the average range typically being about 15% to 90%). The historically adjusted concentration has similar variability and typically ranges from about 35% to 100%.

Conclusions: The study provides evidence of variability in the level of crime concentration across cities, but also raises important questions about the temporal scale when measuring this concentration. The results open an exciting new area of research exploring why levels of crime concentration may vary over cities? Either micro- or macro- theories may help researchers in exploring this new direction.

Keywords: neighborhoods, crime, aggregation, imputation.

Bio

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Young-An Kim is a Ph.D. student in the department of Criminology, Law and Society, at the University of California, Irvine. His research interests focus on crime patterns at micro places, effects of structural characteristics of street segments on crime, and immigration and crime. Besides criminology, he is interested in sociology of health, urban sociology, and quantitative research methods.

Measuring Crime Concentration across Cities of Varying Sizes:

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Scholars have long noted that crime tends to concentrate at various locations within cities, as the tendency of crime to concentrate spatially was observed nearly 200 years ago in Paris, France by Quetelet (1969 (1842)). This concentration tendency is repeatedly observed even as researchers use ever smaller geographic units for aggregating crime counts: from neighborhoods to various census units, down to street segments or even parcels. A question then is whether the level of crime concentration varies over cities? A small, but growing, number of recent studies have detected relatively similar levels of concentration across cities, spurring Weisburd, Groff, and Yang (2012)to propose a "law of crime concentration" in which it is proposed that "for a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime" (Weisburd 2015). This was a bold proposal put forth by these authors, and was echoed in Weisburd's Sutherland speech in 2014 (Weisburd 2015).

The question of how similar the level of crime concentration is across cities poses at least four challenges for researchers. First, there is no agreement regarding how similar the level of concentration should be across cities to be termed "similar". For example, the law of crime concentration states that "…the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime" (Weisburd 2015); yet it is never specified anywhere how narrow this bandwidth must be. Thus, evidence is necessary for the width of this bandwidth. A second question is whether the level of concentration should be compared across cities of different sizes, and/or for different definitions of crime. This raises scope conditions of the proper geographic units when comparing levels of crime concentration, and relates directly to the third issue. The third challenge for assessing crime concentration is a statistical one: simply by random chance a certain amount of crime concentration will be observed in cities. As we will highlight below, the amount will vary over cities, and to some extent it will vary in systematic ways that pose a problem for one technique researchers use to measure the level of crime concentration. We will propose one solution to this challenge, but this raises a fourth issue: how should we measure crime concentration to assess differences across cities? Different measures can be used depending on the temporal assumptions about the stability of crime concentration that the researcher is willing to make, which can have theoretical and empirical implications. This is particularly important when comparing different-sized cities or relatively rare crime types.

Given the need for more robust empirical evidence regarding how consistently crime concentrates across cities, we will provide that here by using data for 42 cities in southern California with at least 40,000 population over an eight year period (2005-12) to explore the level of crime concentration in these cities. We will use three different measures that make different temporal assumptions about the stability of crime concentration, and the differences in the results we obtain across these measures highlight that this is an issue that researchers need to explicitly consider. We will orient our literature review around the proposed Law of crime concentration, as this is the clearest statement on the possible level of crime concentration across cities. We will highlight that there are some intriguing macro theoretical implications if a law of crime concentration is true that deserve consideration. Conversely, there are also interesting theoretical issues if there is in fact variability across cities in the level of crime concentration.

Literature Review

Law of crime concentration
Proper macro-units of analysis?

The law of crime concentration proposes that "for a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime" (Weisburd 2015). There is some uncertainty around this definition. We acknowledge one view is that a law in the social sciences should not be held to the same standards as a law in the physical sciences. For example, Tobler's First Law of Geography that "everything is related to everything else, but near things are more related than distant things" is quite vague. We nonetheless believe a careful consideration of issues regarding *measuring* crime concentration is warranted regardless of one's view of the efficacy of this as a "Law". First, how narrow must a "narrow bandwidth" be? Second, although the law is clear in focusing on any "defined measure of crime," early work on crime concentration often combined all calls for service into a single measure, which may lead some to presume that it only applies to specific aggregations of crime. Some recent work has disaggregated by types of crime (Andresen, Curman, and Linning 2017), although it is unclear whether we should expect to observe similar levels of crime concentration across cities for various crime types.

Third, whereas the law specifically allows for different microgeographic units, it is not specified which larger aggregate unit these smaller units should be aggregated into. In the nascent existing research, scholars typically use a city as the larger unit, and often use extremely large cities (Weisburd, Groff, and Yang 2012)(Weisburd 2014). Will the law hold for all cities, regardless of their size? Or is it only appropriate for very large cities? Furthermore, given that cities are municipal units with politically-defined boundaries, is this really the appropriate unit? City boundaries are somewhat arbitrary, can change over time, and arguably do not really define residents' behavioral patterns. That is, residents often cross city boundaries to work, shop, form friendships, and perhaps even commit crimes. Given all this, are politically defined cities truly the proper larger unit for such comparisons? For example, perhaps some specific distance more appropriately characterizes the macro environment of interest, as suggested by Hipp and Roussell (2013) in their study of the principles of population size and density. Given that the proposed law was formulated based on evidence from research using cities as the larger unit, we will assume that cities are indeed the proper unit and not explore this issue any further here. We simply raise this here as an issue for future consideration in measuring concentration.

Proper micro-units of analysis?

We briefly note that an apparent strength of the proposed law of crime concentrations is that if we use different micro-geographic units we should still expect to obtain results of crime concentration within some small range of values. This is a surprisingly strong claim from a theoretical point of view that is underappreciated, as it proposes that whatever concentration is observed at one level of granularity will be observed at higher levels (albeit with a uniformly lower value of concentration). If true, an implication is that although there is variability across the blocks within larger units, crime will aggregate up in a particularly systematic way such that the level of crime concentration for the larger units will be a ratio of that in the smaller units. This implies that there is some unseen larger force that is binding the level of concentration from the smaller units to the larger units. This implies a particularly complicated process, if the law of crime concentration is true. Given that much of the crime and place literature focuses exclusively on crime within small units of analysis based on the argument that there is considerable variability of crime over small units nested within larger units, this possibility implies a systematic relationship between crime in small units and crime in the larger nesting units. We do not explore this further here, but simply highlight that this is an interesting theoretical implication that has not been given adequate consideration.

Empirical evidence of crime concentration?

At this point, there is only a small, but growing, body of evidence regarding crime concentration across cities (Braga, Papachristos, and Hureau 2010; Curman, Andresen, and Brantingham 2014b; Eck, Gersh, and Taylor 2000; Groff, Weisburd, and Yang 2010a; Sherman, Gartin, and Buerger 1989; Sherman 1995; Spelman 1995; Weisburd and Amram 2014; Weisburd, Bushway, Lum, and Yang 2004; Weisburd, Groff, and Yang 2012; Weisburd and Mazerolle 2000). For example, Sherman, Gartin, and Buerger (1989) found that about 50% of crime calls were attributed to 3.5 percent of the addresses in Minneapolis in a single year. Likewise, Spelman (1995) found that the worst 10 percent of public spaces (high schools, subway stations, public housing projects, and parks) accounted for 50% of crime calls. Weisburd and Mazerolle (2000) found that just 5 percent of the streets in Jersey City showed evidence of drug activity, and the majority of the city was free of drug activity. In a study using crime calls at addresses in the Bronx and Baltimore, Eck, Gersh, and Taylor (2000) found that 10 percent of places produced 32 percent of crime. In their study on gun violence in Boston between 1980 and 2008, Braga, Papachristos, and Hureau (2010) found that less than 3 percent of street segments and intersections produced more than half of incidents of gun violence.

Studies conducted in Seattle by Weisburd and colleagues (Weisburd, Groff, and Yang 2012)(Weisburd, Bushway, Lum, and Yang 2004) confirmed crime concentration at the street segment level and its stability over time. For instance, Weisburd, Bushway, Lum, and Yang (2004) found that 50 percent of calls for service over 14 year period (1989-2002) are attributable to only 4.5 percent of the street segments in Seattle. Curman, Andresen, and Brantingham

(2014b) replicated Weisburd and colleagues studies by examining calls for service in Vancouver, BC, Canada. They found that 60 percent of calls are concentrated at 7.8 percent of street segments and this concentration is stable across time. Although there is evidence of a degree of concentration, more research is necessary. Furthermore, there are statistical issues when assessing crime concentration, to which we turn next.

Statistical challenges to measuring crime concentration

One fundamental challenge to comparing the level of crime concentration across cities is a statistical problem: by random chance we will always observe a certain amount of concentration of crime based on the typical measure used. In this manuscript, for brevity we will focus on the amount of crime that concentrates in the top 5% of segments in a city; nonetheless, the logic of what we consider here extends to other chosen values (e.g., 1%, 2%, etc.). If crime events occurred in a completely random spatial pattern, then if we were to choose at random 5% of the segments in a city we would expect to observe 5% of the crime events; however, the challenge here is more problematic given how the level of crime concentration is assessed. When assessing the crime concentration, the segments of a city are sorted from highest to lowest based on number of crime events and therefore the expected count is in fact the tail of a Poisson distribution based on the number of crime counts in the city and the number of segments. Although it is straightforward to compute the expected counts of crime events in these most extreme segments, most existing research in this nascent literature does not account for this (for an exception, see Levin, Rosenfeld, and Deckard 2015).

This statistical problem is enhanced in cities with relatively low crime levels. In fact, in the extreme case of a city with relatively few crime events 100 percent of crime events will always be observed in 5% of the segments (even with spatial randomness). As an example, consider a city with 100 segments and in which just 5 crime events were observed in the prior year. In this case, even if the crime events are completely random, at most we will observe only 5 segments experience crime events, and therefore 5% of the segments in the city will contain 100% of the crime events. This is, of course, an extreme case. However, an important insight is that as cities approach particularly low numbers of crime events, concentration will be observed even if there is random placement of crime events. This insight has not to this point been appropriately appreciated in the literature, and has consequences when studying cities from a wide spectrum of sizes and crime levels, as we will explore later in this manuscript.

To address this statistical problem, one possible solution is to compare the concentration level observed in the city with what would be observed assuming spatial randomness of crimes in segments in the city.[1] But what do we do next with this information? One possibility would be to assess whether the level of crime concentration in a city is statistically *different* than that expected by chance. To do this, one would generate the expected number of crime events in the top 5% of segments in a city based on the number of crime events and the number of segments in the city (assuming random locations of crime events) as a Monte Carlo simulation. One could then assess where the observed number of crime events in the top 5% of segments in the city lies on this distribution, and determine if the observed concentration is greater than expected based on chance. However, this is a *very weak* test as the notion that crime tends to concentrate spatially is relatively well-known, and furthermore we are most interested in comparing across cities the *level* of concentration of crime.

[1] This spatial randomness assumption is used to construct an appropriate baseline measure; for a discussion of proper baselines, see (Hipp, Tita, and Boggess 2011). And this is consonant with the approach in the literature of assessing the level of crime concentration in cities regardless of the characteristics of smaller geographic units.

Law of crime concentration

Given that we are not interested in simply assessing whether the observed concentration of crime is significantly different than chance, another approach would be to compute the mean and standard deviation of this same Monte Carlo simulation of expected values of crime in segments based on random chance to compute the z-score of the observed level of crime concentration in the city. While this has a certain appeal of assessing *how different* the observed concentration is than chance, a limitation is that z-scores will necessarily be much larger in a city with more crime events and therefore have a tighter distribution around the random counts. In low crime cities, the distribution will be much wider, and the mean plus the standard deviation may even include 100%, or at least be close. In low crime cities, therefore, it would not be possible to obtain a high z-score on the observed crime concentration simply because there is too much uncertainty to assess the level of crime concentration. It therefore may or may not be desirable to capture this precision in the measure that captures the amount of concentration in the city. This approach also has the limitation of not allowing assessments of the *level* of crime concentration across cities.

These considerations suggest the need to distinguish between the true amount of crime concentration in a city, and the amount observed simply due to random chance. The problem is that the traditional approach to measuring crime concentration conflates these two constructs. The challenge then is to disentangle these two constructs given that we are interested in measuring the true amount of crime concentration. If one instead presumes that the observed level of concentration will be the same across cities—and thus cities will have different mixes of true concentration and that due to random change—then the law of crime concentration would need a definition that includes both 1) a true concentration component as well as 2) a statistical chance component. We do not pursue this further given that we are skeptical of the theoretical utility of pursuing this direction, and argue that it is more appropriate to only measure the "true" level of concentration after accounting for this statistical randomness.

Given the challenge of how to account for the random probability that a certain amount of crime will appear concentrated in a small subset of segments, we propose a simpler solution here that is very easy for researchers to implement and raises the issue of *temporal stability* in crime concentration. There is always an implicit temporal component to crime concentration: at a minimum, scholars often impose a one-year stability assumption in counting up the number of crime events that occurred during a particular year and then computing the level of concentration. The crime hot spot literature emphasizes the stability of crime locations, although the temporal period can be identified as a period anywhere from less than a year to much longer than a year (Gorr and Lee 2014; Grubesic and Mack 2008). In our approach we focus on the common longer-term stability, which is what Weisburd and colleagues (Weisburd, Groff, and Yang 2012) noted in their longitudinal study of Seattle street segments. If it wasn't the case that crime generally concentrated in the same segments over repeated time points, this would require a particularly complicated theory to explain why cities not only have the same level of crime concentration over time, but that the crime shifts around to different street segments from year to year. The empirical evidence in general does not support this, and we are aware of no theories positing such a complicated process.

Our solution to account for the randomness of crime location therefore first sorts segments based on level of crime in the *prior year*, and then computes the proportion of crime that these segments account for in the *current year*. We refer to this as *temporally adjusted crime concentration*, and argue that this is a reasonable approximation of the amount of crime concentration in a city that to some extent gets around the random probability problem. We emphasize that this is an approximation, as it is not entirely correct for two reasons: 1) in any given year, there can be certain segments that are not true "high crime" segments, but will simply appear in the top segments because of an increased crime count because of the stochastic nature of crime events; 2) in the following year, although we expect most segments to still be among the highest crime segments, a certain small percentage may legitimately stop being among the highest crime segments. Our approach will inadvertently include these two types of segments as those expected to be among the highest crime segments in a given year. This is not terribly problematic because we argue that: 1) in any given year, such segments should constitute a very small percentage of the highest crime segments (based on the hot spot logic articulated earlier); 2) we have no reason to expect that the number of segments of these two types would differ considerably over cities, and therefore our estimate of the level of crime concentration would be uniformly modestly underestimated across all cities; this would still allow us to compare whether the level of concentration is the *same* across cities. As a sidenote, we point out that if assumption #2 is not accurate, this would imply a need for theorizing why some cities have many more segments that are ceasing to be high crime segments from year to year compared to other cities.[2] Presumably, this theory would either: 1) propose structural or cultural characteristics of a city that lead to a constant state of such flux; or 2) propose why a city is undergoing a structural or cultural change at one point in time that leads to a short-term period in which the location of crime concentration changes. This would almost certainly require macro-level theorizing to explain either of these scenarios.[3]

[2] Given that random chance is driving those in the first category of segments—those that have an unexpectedly high number of crimes in a particular year—it is extremely unlikely that there would be something systematically driving this. If there is something systematic about them, this would imply that they instead belong in the second category, as they were legitimately high crime segments in one year but then changed the following year.

[3] If one wished to construct a theory at the level of the micro-units, one would need to posit at least two classes of high crime street segments: 1) consistently high crime segments; 2) variable high crime segments. And this would

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We note that another approach existing in the literature to assess the level of crime concentration at least implicitly addresses this randomness of crime events by utilizing a group based modeling approach (Curman, Andresen, and Brantingham 2014a; Weisburd, Bushway, Lum, and Yang 2004). This strategy uses data from a particular city over a number of years and latent groups are detected that have distinct crime patterns over time (Muthén and Muthén 2000; Nagin 1999). The researcher can then select the group(s) with consistently high crime counts over time. This descriptive approach shows the percentage of crime events that are in the percentage of segments in the city contained in these high crime count groups. In this retrospective approach the level of crime concentration and the group identification are both computed on the same years of data. This strategy detects general consistency from year to year in the level of crime for a street segment, which is captured by the latent group measures. There is uncertainty how to handle groups in which the segments show strong increases or decreases in crime over the period: does one include them among the "highest" crime segments in all years, or just the years that their group has relatively high crime levels? We sidestep this issue by adopting an analogous approach: we sum the total number of crime events (for each crime type) in each segment over all years, and then determine the top 5% of segments for a particular crime type based on this measure. We refer to this as *historically adjusted crime concentration*.

What are the theoretical implications of a law of crime concentration?

If the law of crime concentration is true, a counterintuitive implication is that there is no variability to explain. Social science research typically focuses on variance across units, and attempts to "explain" it. Weisburd et al. (2012) revealed that there is a street-to-street variability

require an explanation for the existence of these latter segments that vary between high and low crime levels from year to year. Whereas most existing micro-geography theories explain why some locations have more or less crime, this would instead require a theory of some characteristic(s) that cause certain locations to be locked in an equilibrium in which they fluctuate between high and low crime levels from year to year. We are aware of no such theory.

of crime as well as criminal opportunities and structural characteristics. They hypothesized and tested whether these factors impact crime rates and stability in street segments and stated that "a large array of opportunity and social disorganization measures influence the likelihood of a street segment being in the chronic-crime pattern" (p.160). But what does it mean if the total variability across the smaller units within a larger unit is constrained by some force to be a specific value? Does this make the study of variance at smaller units obsolete? Let us consider this issue.

Consider a stylized example in which there is some variable X that entirely explains the amount of crime in segments. Suppose, for example, that segments containing this variable have ten times as much crime as segments without this variable. One implication is that the composition of segments with such a feature within a city will explain the amount of crime in the city. Thus, a city that has more segments with variable X will have higher crime on these segments, and this will sum up to more crime in the city. But this also has implications for the level of concentration of crime in the segments within a city.

For example, consider two hypothetical cities, A and B. These are shown in Figure 1, and in city A 5% of the segments contain high concentrations of variable X (1 of the 20 units). These segments will have 10-fold more crime than the other segments in the city. And this will result in a certain level of concentration of crime in these segments. But consider city B in which 30% of the segments contain a high concentration of variable X (6 of the 20 units). We would expect these segments to have 10-fold more crime than the other segments in the city. However, a consequence is that the level of crime concentration in city B will be different than that in city A. Given that variable X increases crime 10-fold in those segments, then city A will not only have less overall crime than city B, but the crime it has will be more concentrated

(34.5% of the crime in the top 5% of segments compared to 13.5% for city B).[4] Note that if we posited a more complicated model in which crime is a function of many variables, the example becomes more complicated; however, it is nonetheless still trivial to construct cities that differ in composition of the measures of interest, and therefore would be expected to have different levels of crime concentration.

<<<Figure 1 about here>>>

How to avoid this theoretical dilemma? One theoretical approach would be a very complicated theory of multiple determinants of crime, but in which there is also some larger functional process that leads all cities to have the "proper" mix of these variables that yields a similar level of crime concentration. This is clearly a quite complicated theory, and there is certainly no such theory existing in the literature. Note as well that such a functional theory necessarily would exist at the level of the city, a large geographic unit that is typically not the purview of much research on crime and place. A second theoretical approach would be to presume that whereas a measure such as X indeed has a positive impact on the amount of crime in the segment, the *relative* level of increased crime would differ depending on the city context. In our stylized example, if the effect of variable X in city B was still a 10-fold increase in crime in the segments, city A would require a 3-fold increase in crime in the segment to have an equal 13.5% concentration of crime. Again, we are not aware of any existing theories that posit such a cross-level interaction in which the effect of a measure at the segment level differs fundamentally based on the composition of the measure in the city overall. Nonetheless, the implication is that, if such a law exists, scholars will need to construct theories that explicitly

[4] In city A, 1 segment has 10 crime incidents and the other 19 have 1, thus: (1*10)+(19*1) = 29 crime incidents. The one segment (the top 5%) has 10/29 of the crime incidents, or 34.5%. In city B, 6 segments have 10 incidents and the other 14 have 1, thus: (6*10)+(14*1) = 74 crime incidents. The top segment (the top 5%), has 10/74 of the crime incidents, or 13.5%.

take into account macro characteristics of cities. Researchers would therefore need to not only theorize such cross-level interactions, but to test them as well.

A third theoretical possibility is that there is in fact no such variable X that explains the location of crime on specific segments. This would certainly be a disheartening implication for theories such as crime patterning theory that focus on why crime occurs in some locations and not others. In this scenario, the structural process that gives rise to a specific level of crime concentration in cities would exist entirely at the level of the city. Given the empirical body of evidence focusing on local characteristics that are associated with the existence of more crime at certain localities, we find this possibility particularly unlikely.

The above considerations suggest that a law of crime concentration—as stated—would certainly be a large challenge to criminological ecological theory if such a law is true. For these reasons—and given that there is limited empirical evidence regarding the law of crime concentration and uncertainty regarding which concentration measure to use and which macro units to use—we empirically explore it here with a large sample of cities in the southern California region. Our empirical tests also account for the random probability that a certain degree of concentration will always be observed.

Data and methods

Data

The crime data come from a large number of police agencies in the southern California region. The 42 cities included in the study with at least 40,000 population are shown in Appendix Table A4; in ancillary models all 82 cities with at least 10,000 population are used. The data come from crime reports officially coded and reported by the police departments. We classified crime events into five Uniform Crime Report (UCR) crime types: aggravated assault, robbery, burglary, motor vehicle theft, and larceny. We do not include homicides given the rareness of these events in these cities. We also computed a measure of total Part 1 crime events for these six crime types (including homicides), for an approximate comparison to studies using the more inclusive measure of calls for service in a city. We used crime data from 2005-2012 given that these years provide us the largest sample of cities (some cities do not have more recent data, and only a smaller number have data from 2000-04). Given that we know the actual location of the crime event, we are able to locate these events to specific street segments.

Crime events were geocoded for each city separately to latitude–longitude point locations using a geographic information system (ArcGIS 10.2) and placed to the nearest street segments based on geographic proximity. The geocoding match rate was 97.2% over these cities, with the lowest value at 91.4%. Previous studies have sometimes excluded calls for service that occurred at intersections. The reasons for doing this were (1) since the events at intersections could be considered part of any one of the participating street segments, there is no clear method for assigning them to one or another; and (2) incident reports at intersections differed dramatically from those at street segments (Weisburd et al. 2012; Weisburd et al. 2014). However, in our crime data the characteristics of crime at intersections are not different from those at street segments, therefore dropping them is not appropriate. Thus, for the 2.2 percent of events at intersections, we evenly assigned them to contiguous street segments. For example, if a crime incident occurred on a typical intersection where two roads cross, each of the four segments is assigned 0.25 of a crime.

Table A1 in the Appendix shows the summary statistics for the 42 cities used in the primary analyses. There is considerable variability: the average household income over these cities ranges from about $46,000 to $156,000. The cities, on average, are about 5% black, although they range from 0% to 33% black. The cities are, on average, 41.5% Latino, ranging from 9% to almost all Latino. And whereas in the average city about 29% of the population has at least a bachelor's degree, this ranges from 4 to 66%. And the average city has about 175,000 population, ranging from cities with 40,000 population up to Los Angeles (with 3.7 million). Table A2 presents the crime counts for the cities available in each of the years of the analyses. These tables show that we have considerable variability across these cities for assessing the level of crime concentration.

Methods

We first geocoded each crime incident to a specific street segment. Then, to measure unadjusted crime concentration for each city we computed the number of crime events (of our five Part 1 crime types and the combined total crime measure) that occurred on each segment in each year of the study. For each city, we then sorted the segments based on the number of crime events of a specific type (from highest to lowest) in a particular year, and computed the percent of overall crime events that occurred on the top 5% of segments.

To assess the random probability of crime concentration, we adopted a small Monte Carlo simulation. For each city, we divided the crime count for a particular year by the number of segments, which yielded the mean number of crime events in each segment. We then generated the expected number of crime events in each segment from a Poisson distribution using this expected mean for each segment. This approach uses the probability integral transform methods of Kemp and Kemp (Kemp and Kemp 1990; Kemp and Kemp 1991), and is hardcoded in Stata 13.1. After generating the number of crime events in each segment based on this simulation, we sorted the segments from highest to lowest crime events and computed the percent of overall crime events in the 5% of segments with the most crime. We repeated this simulation and the calculations 10 times for each city to smooth random variability over simulations; we computed the mean number of crime events contained in these top 5% of segments over the 10 simulations.

As a third way of assessing crime concentration, we used an approach analogous to studies using growth mixture models to determine high crime segments based on information from all years of crime data. In this *historically adjusted crime concentration* measure we: 1) sorted the segments based on the number of crime events of a specific type (from highest to lowest) over all available years, and then 2) computed the percent of overall crime events that occurred on the top 5% of segments in the current year. This approach uses information from all years to assess high crime segments in a particular year, and therefore it does not entirely address the random probability of crime concentration issue.

As a fourth way of assessing crime concentration, we used our preferred approach that we refer to as *temporally adjusted crime concentration* in which we: 1) sorted the segments based on the number of crime events of a specific type (from highest to lowest) in the *prior* year, and then 2) computed the percent of overall crime events that occurred on the top 5% of segments in the *current* year. Note that this approach requires crime data from the prior year; therefore, it cannot be calculated in cities for the first year in which crime data are available. Therefore this measure in our tables will have fewer cities in some years compared to the traditional approach to assessing crime concentration.

We performed the above computations on all cities in our study with at least 40,000 population. We also performed the computations on all cities in the study with at least 10,000 population and present these ancillary results in the Appendix to demonstrate the results when using very small population cities. Finally, we also present the results for the 16 cities with at least 100,000 population to describe the pattern for relatively large cities.

Although our primary focus is on these descriptive results showing the differences in crime concentration across cities, we also demonstrate the problem of not accounting for the random distribution of crime events when using the traditional measure. We accomplish this by demonstrating that including only measures of size of city and number of crime events explains a relatively large proportion of the difference in this measure across cities. We estimated linear regression models in which the units of analysis were cities and the outcome variable was the unadjusted percentage of crime in the top 5% of segments in the city. These models included just three covariates: 1) the number of crime segments in the city; 2) the count of crimes of that type in the city in that year; 3) an interaction between these two measures.

Results

We begin by showing the amount of crime concentration in the 5% of street segments with the most crime among cities with at least 40,000 population; this is the standard approach for assessing such concentration and does not account for the random distribution of crime (Table A3 in the Appendix shows the results for all cities with at least 10,000 population). In Table 1, the first column shows the year, the second column shows the number of cities we had data for in that year, and the third column shows the mean percentage of aggravated assaults that occurred in the top 5% of the segments over these cities. Thus, in 2005 we had 23 cities, and in the average city a very high 94.8% of the aggravated assaults occurred in the top 5% of the segments. However, note that the standard deviation in the amount of concentration over these cities is 11.3%: thus, if the crime concentration levels were a normal distribution, we'd expect that 2/3 of the cities would have between 72% and 100% crime concentration. Of course, the maximum value can be 100%, which is indeed what we observe in a number of cities.

<<<Table 1 about here>>>

As we move down the rows for the other years, we see that the results for aggravated assault are quite consistent: the mean level of crime concentration ranges from 92.6% to 96%, the standard deviation ranges from 7.7% to 12.1%, and the minimum value ranges from 61.6% to 72.1%, and the maximum value is always 100%. Thus, there appears to be a high amount of concentration for aggravated assault (over 90%) for this standard measure.

However, as we argued earlier, a problem with these results using the traditional approach to computing concentration is that they do not account for the fact that we would expect to see a certain level of concentration simply based on random chance. To address this, in the bottom panel of Table 1 we present the results from our temporally adjusted crime concentration measure. Here, we see much smaller values for the level of concentration of aggravated assault. In 2005, the mean level of concentration for aggravated assault is just 33.2% over these cities (60 percentage points lower than the unadjusted estimate from the top of Table 1). There is still considerable variability over these cities, with a standard deviation of 16.5% in 2005. Most notably, the range of values is quite extreme over cities: from 16.2% to 100%. And looking at the other years we see the same pattern for aggravated assault: the mean value over these years ranges from 26.2% to 33.2%, the standard deviation ranges from 12.3% to 16.5%, and the range is from less than 10% to 100% in most years across cities.

The middle panel of Table 1 presents the results for the historically adjusted crime concentration measure (that uses information from all years to determine the highest crime segments). For aggravated assault, the average level of concentration over these years (66.8%) is about midway between the value for the unadjusted measure (94.3%) and the temporally adjusted measure (29.3%). Importantly, there is considerable variability across these cities even when using this concentration measure as the average standard deviation over these years is 16.2% and the range is about 40% to 100%.

Turning to the other violent crime studied here—robbery—we see that this crime appears even more concentrated based on the standard measure of crime concentration. The mean percentage of robberies that occur in the top 5% of segments across these cities is 96% in 2005, and ranges from 94.3% to 98.5% over these years. The standard deviation over these cities is narrower than for aggravated assaults, although this is because the higher mean bumps up against the maximum possible value of 100% and therefore constrains the variability. In the bottom part of Table 1 we see that the degree of concentration based on the temporally adjusted crime concentration measure is again considerably lower than the unadjusted measure. The mean level of robbery concentration over these years ranges from 36% to 43.2%. Thus, this temporal adjustment provides a very different picture of the amount of robbery concentration. In part, this is because robbery is a relatively rare event compared to the other crime types studied here, and as a result we expect a higher concentration of robberies simply based on random chance. Notably, the historically adjusted concentration measure (the middle panel) demonstrates very high average concentration of 82% over these years. Nonetheless, the range of values across cities in the top 5% of segments based on this definition is about 50% to 100%, with an average standard deviation of 17% across these years.

Turning to the property crimes, we see that burglary shows less crime concentration, on average, compared to the violent crimes when using the traditional crime concentration measure. We see that, on average over these cities, 71.8% of burglary events occur in the top 5% of segments over the study period. The average standard deviation over years in the cities is 18%, so there is considerable variability across cities in this concentration. The fact that the city with the least concentration is typically around 45% in these years is also evidence of this variability.

We highlight an important point: whereas one might be inclined to conclude that a property crime such as burglary exhibits less concentration than the violent crimes based on the top panel of Table 1—and perhaps construct theories regarding the inherently more geographically concentrated nature of violent crime—the bottom panel of Table 1 shows that this difference evaporates when temporally adjusting the measure of concentration. In fact, the average temporally adjusted concentration of burglary over these years is 34.9%, which is only a little bit below robbery (39.3%) and slightly higher than aggravated assault (29.3%). In the middle panel, the historically adjusted measure again shows considerable variability over these cities with the percent of crime contained in the top 5% of segments ranging from about 30% to 100% across cities over these years.

For motor vehicle theft, whereas we see that it exhibits somewhat higher concentration than burglary using the unadjusted measure (79.9% on average over these years), the temporally adjusted level of concentration for motor vehicle theft is very similar to that for burglary. Over these years, the mean level of temporally adjusted concentration for motor vehicle theft is 35.1% with a standard deviation of 15.7% over these cities. Once again, the average level of historically adjusted crime concentration (the middle panel) is somewhere between the unadjusted and temporally adjusted measures. Nonetheless, even this approach demonstrates considerable variability across cities, with the top 5% of segments accounting for between 30% and 100% of the crime across these cities.

The results for larceny follow a similar pattern to the other crime types, with an interesting twist. Whereas larceny appears to be the least concentrated type of crime studied here when using the traditional measure of crime concentration—the unadjusted measure shows that the average city over the years of the study experiences 59.8% of larcenies in the top 5% of segments, which is lower than the other four crime types—it actually has the *highest* level of concentration when using our temporally adjusted measure. When temporally adjusting larceny, we find that the top 5% of segments contain 50.8% of the larcenies, on average, over these years. This is a higher percentage than all four of the other types of crime. Thus, not only is it important to temporally adjust the measure of crime concentration—as our results show that the estimate of crime concentration can be reduced between 30 and 60 percentage points for the various crime types—but the results for larceny illuminate as well that the level of concentration will not be reduced uniformly across crime types when temporally adjusting, but rather the reduction can actually differ a fair amount. In this case, our conclusion of which crime type exhibits the highest concentration is completely reversed based on using this temporal adjustment. The results are different yet with the historically adjusted concentration measure, as the level of concentration for some crime types (particularly aggravated assault) get reduced more from the unadjusted measure compared to other crime types (i.e., robbery and larceny). Thus, robbery appears to have the highest concentration with the historically adjusted measure.

Finally, we turn to the measures of concentration for total crimes, to assess the extent to which the patterns we have observed are driven by disaggregating crime types. This higher aggregation lowers the unadjusted concentration measures modestly because the crime counts are now higher and therefore the impact of random crime events does not as strongly impact these measures. The average unadjusted concentration of total crimes is 59.8% over these years, which is lower than any of the specific crime types. But the temporally adjusted concentration of total crime is 48.3% over these years, which is similar to the value for larceny. We observe considerable variability across these cities in the level of concentration even when aggregating to total crime: the unadjusted measure has an average standard deviation of 11.7% and an average range from 40 to 100% across these years. The temporally adjusted measure has an average standard deviation of 12.3%, and an average range from 26% to 96%, suggesting considerable variability. Based on the historically adjusted measure (the middle panel), the average total crime concentration across years is 53.5%, with an average standard deviation of 11.5%. This definition also has considerable variability across cities in the level of concentration for total crime, ranging from about 33% to 100% across years.

There is clearly considerable variability in the level of crime concentration across these cities over all of these crime types. We next demonstrate how much of this variability in the unadjusted crime concentration can be explained by the size of the city and the frequency of crime events.

Simple models explaining the level of crime concentration

Given that we have observed considerable variability in the level of unadjusted crime concentration, we use very simple models to illustrate the extent to which the level of unadjusted crime concentration is driven by random processes (by including only information on the number of crime events and the number of segments in a city). The outcome variable is the percent crime concentration for a particular crime type in a particular city in a particular year. The results are shown in Table 2 for cities with at least 40,000 population.

<<<Table 2 about here>>>

Law of crime concentration

It is notable that this simple model explains between 34% and 75% of the variance in the level of unadjusted crime concentration in a city. This highlights the problem of using an unadjusted measure of crime concentration, given that in cities with low crime counts the random probability of placement of crime events can largely impact this measure. The variance explained is somewhat lower for total crime, but still substantial as the model explains 43% of the variance. In all of these models the level of concentration decreases as the number of crime events increases in the city. And the level of concentration increases as the number of segments increases (given that there will be more segments in the top 5%, by definition, which will increase the expected concentration for a set number of crime events). And the interaction is positive for all models.

As a comparison, we estimated similar models for the historically adjusted concentration measure, and the middle rows of this table show the R-square results for these models 7-12. For each crime type we see that the R-square is reduced somewhat when defining crime based on all years compared to the unadjusted measure. Nonetheless, this approach does not entirely account for the random nature of crime events, as these simple models containing city size and number of crime events explain between 16 and 59% of the variance in crime concentration across cities. The bottom two rows of Table 2 show the R-squares for the same models estimated on the temporally adjusted measure of crime concentration. In these models, the three covariates are only sometimes statistically significant. And the variance explained is just 4-12% for the 5 crime types, and 18% for total crime. Thus, our temporally adjusted crime concentration measure is largely accounting for these random processes that are driven by the number of crime events per segment in a city.

What do high and low crime concentration cities look like?

Law of crime concentration

Given that we observed considerable variability in the crime concentration of these cities in a particular year, do the specific cities exhibit consistency over time regarding high or low levels of concentration? In the top panel of Table 3, of cities with at least 40,000 population we list the 10 lowest temporally adjusted aggravated assault concentration values averaged over the years of the study. Values are missing for years in which we did not have crime data. The first column shows the population of the city in 2010, and we can see that these are fairly substantially sized cities. Two of these cities have more than 100,000 population. The second column shows the number of segments in the city, the third column lists the number of aggravated assault events in the city in 2010, and the fourth column lists the percentage of these events that are contained in the highest 5% of segments in 2010. We can see that although these cities represent relatively low adjusted crime concentration, the unadjusted crime concentration values are all 100% for these cities. The fifth column helps in explaining this result: this shows the expected level of concentration based on random chance in 2010. For these cities the value is in fact 100%. Thus, the high concentration of aggravated assault in these cities is not a substantive indication of the tendency for crime to concentrate in these cities, but rather simply a statistical anomaly of the strategy of computing unadjusted crime concentration values.

<<<Table 3 about here>>>

Note that many of these cities have quite low values of temporally adjusted concentration. For example, Redondo Beach has a population of 66,000 and is below 18% in all years (and below 10% in several years). Thus, this is a beach city that consistently exhibits quite low temporally adjusted aggravated assault concentration. San Clemente is another beach city that has very low values in most years. Corona is an inland city that is typically below 25% concentration. Given that low concentration cities include the low crime city of Laguna Niguel and the relatively high crime city of Colton implies that a single characteristic does not seem to describe these low aggravated assault concentration cities.

In the bottom half of Table 3, we list cities with at least 40,000 population and the top 10 *highest* average temporally adjusted aggravated assault concentration values over the study period. These cities typically have relatively consistent adjusted concentration values. Yorba Linda, a low crime city, is particularly notable in experiencing aggravated assaults in the same locations over years. Escondido, a city with 140,000 population, is consistently between 50 and 60% adjusted concentration over years, which contrasts with large cities such as Irvine and Corona in the top panel of this table. Note that Irvine (100%) and Corona (about 70%) have historically adjusted aggravated assault concentration that is similar to that of Escondido (about 70%), again highlighting the importance of how crime concentration is defined.

Table 4 presents the high and low concentration cities for burglary, and the top panel lists cities that consistently exhibit quite low levels of burglary concentration when using our temporally adjusted measure. Again, simply using the unadjusted measure would lead to the inappropriate conclusion of a high level of burglary concentration. Much of this apparent concentration is simply driven by random chance, which can be seen by comparing the results for 2010 in columns 4 and 5, which show that the expected percentage of concentration is often nearly as high as the observed percentage. On the other hand, the bottom panel of this table lists cities that consistently have considerably higher levels of burglary concentration based on the temporally adjusted measure. In these cities, although the number of crime events in the most extreme segments is not very much larger than expected by chance—which may lead to a presumption that randomness is driving the process—the higher values of the temporally adjusted concentration measure highlight that these burglaries are generally occurring in the same set of segments from year to year. Thus, whereas the cities in the top panel have temporally adjusted crime concentration levels consistently below 30% or even below 20%, the ones in the bottom panel are typically above 40%, or even 50%. This difference is also present for several of the cities when using historically adjusted concentration.

<<<Table 4 about here>>>

Table 5 presents the high and low concentration cities for total crime. In the top panel there are seven cities with an average temporally adjusted concentration value of 40% or less, whereas in the bottom panel the low crime city of Yorba Linda is above 90% and two other cities are above 60%. And these cities typically exhibit quite consistent levels of total crime concentration over the years of the study. This gap is also evident in the historically adjusted measure, as five cities have average concentration values of 42% or less, whereas six have values of 60% or more. Furthermore, although the conflation of randomness is much less present when using total crime compared to the individual crime types (given the larger number of events) as the expected percentage in the top 5% of segments is often below 20%, it is still the case that the level of crime concentration for the unadjusted measure is considerably higher among the bottom panel cities compared to those in the top panel.

<<<Table 5 about here>>>

Finally, our study has provided evidence regarding the level of crime concentration across cities with a range of population values. Nonetheless, in our final table we present results for the total crime concentration of just the larger cities in our sample (those with at least 100,000 population), given that initial work regarding the level of crime concentration has tended to focus exclusively on very large cities (Curman, Andresen, and Brantingham 2014a; Groff, Weisburd, and Yang 2010b). Even among these relatively large cities, and when measuring total crime, we see considerable variability in the level of concentration over these years. Based on our temporally adjusted concentration measure, nine cities have average values less than 30% over the study period, whereas one city is above 50% and two other cities are above 40%. There is also notable variability for the historically adjusted measure: whereas six cities have concentration values above 70%, six have values of 55% or below. The low crime city of Irvine is notable in having extremely high unadjusted concentration and based on all years of data (100%), but having the lowest average temporally adjusted concentration value.

<<<Table 6 about here>>>

Conclusion

This study has explored the level of crime concentration across 42 cities of varying sizes, and showed that not only is there notable concentration of crime in all cities, there nonetheless is variability across cities in the level of this concentration. Although this study has provided considerable empirical evidence, it has also raised important theoretical questions. We have highlighted that a very large measurement challenge for assessing crime concentration is that by random chance a nontrivial amount of concentration will be observed in cities, and this random component will vary over cities in systematic ways that researchers need to take into account in order to arrive at proper conclusions regarding their data. The use of different-sized cities raised the question of whether crime concentration should indeed be similar over a wide range of city sizes. And in addressing the random component problem of concentration, we raised the theoretical challenge of the temporal stability assumption employed when assessing crime concentration. We also explored some of the counterintuitive theoretical implications if such a law of crime concentration indeed exists.

Law of crime concentration

Our results highlighted that although there is clearly considerable concentration in the level of crime within cities, there is nonetheless a considerable amount of variability in the concentration of crime *across* these cities. We found that this variability across cities in crime concentration was present for virtually every type of crime we studied, and it was present when we created a combined measure of total Part 1 crimes. Furthermore, we showed that whereas certain cities consistently exhibit relatively high levels of temporally adjusted crime concentration, there are also cities that consistently exhibit relatively low levels. This variability was present for the three different measures of crime concentration we used that made different temporal assumptions about the stability of crime.

A second important takeaway point is that researchers should give more consideration to the choice of the macro unit of analysis when exploring the level of crime concentration across cities. Should the level of crime concentration be constant across cities of different sizes? Only minimal consideration has been given to this issue: Weisburd (2014) compared a handful of very large cities to a handful of what he described as smaller cities (though they had population levels near 100,000). But cities come in a wide variety of sizes, and more consideration is needed whether crime concentration should indeed be invariant across such different sized cities. This is not a trivial issue, as we highlighted that there are statistical issues that can confound comparisons of crime concentration across cities of different sizes.

We have emphasized that the size of the macro units used when assessing the level of crime concentration has important implications given the statistical anomaly that many measures of crime concentration will have positive values simply due to random chance. We demonstrated that the measure of crime concentration based on the current year does not satisfactorily account for this concentration based on random chance: for a number of cities and a number of crime types the expected crime concentration based on random chance was just as high as the actual value observed. We also demonstrated that a simple model using the number of crime events and the number of segments in a city can explain between 30 and 60% of the variability in this measure across cities for different crime types. Clearly, this is not a very clean measure for capturing the true level of crime concentration in a city.

In addressing this statistical problem of the random probability of crime concentration, we raised the parallel issue of the temporal aspect of crime concentration. This is a theoretical question that needs more consideration. Weisburd and colleagues (Weisburd, Bushway, Lum, and Yang 2004) highlighted that not only is crime concentration observed across multiple years, but it is also often observed in the *same street segments*. We have highlighted that the temporal assumption made regarding the stability of high crime locations when constructing a concentration measure can lead to different conclusions. We constructed three different concentration measures: one based on the level of crime in that year, a historically adjusted concentration measure that assumes stability in high crime segments over the period of the study, and a novel temporally adjusted measure we proposed that assumes stability from the prior year. We showed that although the first measure makes no assumption about the stability of high crime locations over years, it is strongly impacted by the random probability of crime concentration. And although variants of the historically adjusted measure have been used in the literature, it has some peculiarities. One issue is that it does not fully account for the random probability problem. Another issue is that there is uncertain theoretical justification for using the specific years in which data is available for constructing the measure, as there is no guarantee that one would obtain similar results if a different set of years were used for defining high crime locations. We have argued that although our temporally adjusted measure is not a perfect estimate of the level of crime concentration—as it likely provides a slight underestimate—the level of underestimate should be relatively similar across cities allowing for useful comparisons across cities. And as we noted earlier, if the underestimate of this measure is not uniform across cities, this would open new research areas to understand why certain street segments are not the consistently high crime locations that are typically identified in the crime and place literature, but are instead consistently *fluctuating* high and low crime locations. Although we are skeptical that such locations exist, this suggests another useful avenue for future research. Nonetheless, this measure does assume that there is stability from year to year in high crime locations, which is a specific type of crime concentration.

A general challenge for measuring crime concentration that is worth highlighting is the issue of sparse data. This can occur do to a combination of: a small city, a city with relatively few crimes, or a narrow definition of "crime." This issue has not received proper attention in the crime concentration literature, and comes to the fore in our analyses here. It is worth noting that this was not as much of an issue in early work by Weisburd and colleagues assessing crime concentration given that they used a very large city along with a more expansive definition of crime (calls for service). Whereas using a broad definition of crime helps address the sparse data problem, it raises a conceptual problem: how reasonable is it to assume that all the different types of events that are included in a calls for service measure indeed demonstrate the same spatial pattern (which is the assumption when using such a single measure)? Disaggregating such crime types is likely appropriate if different types of crime concentrate in different locations, and may result in even higher concentration levels observed (albeit raising the sparse data problem). We note that our temporally adjusted measure may also be impacted by sparse data: the measure of high crime segments in one year will have more measurement error in a sparse data scenario, which would presumably systematically reduce the value of the observed concentration measure. It was reassuring that our models explaining the variability in the temporally adjusted measure across cities found that sparseness explained a relatively small amount of variance; nonetheless, this is an issue that needs more consideration.

These questions about the proper temporal stability to observe crime concentration lead directly into several useful theoretical directions spawned by the proposed law of crime concentration. We described some challenging theoretical implications if the law of crime concentration were true. What was particularly notable was that the theoretical explanations were quite likely to come from understanding larger macro geographic units that would give rise to this regularity. Given the explicit focus on micro-geographic units in much of the crime and place research, this is a fascinating implication that possible key insights for this sub-area would require theories at *larger geographic units*. And if there is indeed considerable variability in the level of crime concentration across cities, as our empirical analyses showed, this raises a challenging and exciting theoretical avenue to *explain* these differences. For example, one multilevel study found that there is nontrivial variance in concentration at the level of the city (Steenbeek and Weisburd 2015). Note that one possibility is that these differences could be explained entirely by micro-geographic theories: thus, the fact that levels of crime concentration differ over cities could be simply due to different compositions of smaller units within the city. Indeed, we pointed out that these different compositions pose a particular challenge for the law's hypothesis that the level of concentration will be similar across cities. On the other hand, we cannot rule out the possibility that there may be macro explanations for why the level of crime concentration differs over cities. Although we are agnostic here in which direction future research should take in trying to understand the level of variability in crime concentration across cities, the useful theoretical insight one can glean from the proposed law of crime concentration is that researchers need to use a wider geographic lens in understanding the geographic distribution of crime.

We acknowledge some limitations to this study. First, we limited our study to only cities in southern California. Although the law of crime concentration makes the fundamental claim that it will be observed in all locations, we may be detecting scope conditions regarding a type of area in which it does not hold. Second, we also were limited to data over a relatively short period at one particular point in time (2005-12). Although this did allow us to observe these cities over a number of years, and the law of crime concentration presumably is invariant over epochs, this should be kept in mind as researchers move forward in exploring why crime concentrates more in some cities compared to others.

We believe the study of the amount of crime concentration across cities is very valuable. We found evidence of distinct differences across cities, and we believe this opens up an area of research to understand *why* the level of concentration varies across cities. We have highlighted the challenge of defining the temporal stability assumption that is employed when measuring crime concentration, and how this can impact the conclusions that are drawn in such studies. As researchers compare concentration across cities of different spatial scales, care must be taken when striking a balance between the conceptual problem of defining crime too broadly and the statistical problem of measuring concentration when there are relatively few events. Nonetheless, we believe the variability in crime concentration across cities is a useful avenue to explore, and it may force micro and macro geographic theories of crime to seriously consider each other.

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Tables and Figures

Table 1. Crime clustering for cities with at least 40,000 population, by five types of crime and total Part 1 crimes

	Aggravated assault					Robbery					Burglary				
Percent of crime in segments in top 5% of crime in current year (unadjusted concentration)															
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
2005	23	94.8%	11.3%	65.7%	100.0%	23	96.0%	9.4%	69.2%	100.0%	22	76.9%	20.0%	44.4%	100.0%
2006	25	93.4%	12.1%	62.3%	100.0%	25	94.3%	11.2%	66.0%	100.0%	24	71.9%	19.3%	43.1%	100.0%
2007	39	94.2%	10.6%	61.6%	100.0%	39	95.1%	10.1%	65.3%	100.0%	38	70.1%	17.4%	41.3%	100.0%
2008	39	92.6%	11.5%	64.3%	100.0%	38	95.5%	9.4%	67.5%	100.0%	38	71.1%	17.6%	45.5%	100.0%
2009	40	94.2%	10.4%	67.0%	100.0%	40	96.2%	8.9%	64.4%	100.0%	39	70.7%	16.9%	46.7%	100.0%
2010	41	93.6%	10.8%	66.4%	100.0%	41	97.3%	7.5%	67.2%	100.0%	40	70.9%	17.1%	46.6%	100.0%
2011	42	95.4%	8.1%	72.1%	100.0%	42	98.3%	5.1%	76.8%	100.0%	41	70.4%	17.4%	46.2%	100.0%
2012	33	96.0%	7.7%	70.0%	100.0%	32	98.5%	4.4%	83.3%	100.0%	33	72.5%	19.2%	44.1%	100.0%
Average		94.3%	10.3%	66.2%	100.0%		96.4%	8.3%	70.0%	100.0%		71.8%	18.1%	44.7%	100.0%
Percent of crime in segments in top 5% of crime over all years (historically adjusted concentration)															
2005	23	69.3%	18.7%	44.2%	100.0%	23	84.7%	18.1%	51.0%	100.0%	22	52.2%	14.4%	36.8%	100.0%
2006	25	66.2%	17.9%	41.3%	100.0%	25	83.0%	17.9%	50.2%	100.0%	24	51.9%	14.2%	31.7%	100.0%
2007	39	66.9%	15.1%	43.5%	100.0%	39	82.0%	16.6%	48.9%	100.0%	38	51.2%	12.6%	29.9%	100.0%
2008	39	67.8%	14.2%	47.0%	100.0%	38	80.7%	16.5%	49.2%	100.0%	38	52.0%	13.1%	25.4%	100.0%
2009	40	67.2%	15.5%	44.6%	100.0%	40	81.9%	16.6%	49.5%	100.0%	39	49.5%	12.0%	30.5%	100.0%
2010	41	67.0%	15.4%	38.6%	100.0%	41	81.9%	16.4%	43.8%	100.0%	40	50.1%	11.9%	28.8%	100.0%
2011	42	67.4%	15.5%	43.9%	100.0%	42	81.4%	16.9%	43.7%	100.0%	41	49.7%	12.4%	25.9%	100.0%
2012	33	62.5%	17.6%	0.0%	100.0%	32	82.3%	16.5%	50.9%	100.0%	33	47.2%	18.1%	0.0%	100.0%
Average		66.8%	16.2%	37.9%	100.0%		82.2%	16.9%	48.4%	100.0%		50.5%	13.6%	26.1%	100.0%
Percent of crime in segments in top 5% of crime in prior year (temporally adjusted concentration)															
2005	22	33.2%	16.5%	16.2%	100.0%	22	43.2%	17.9%	11.1%	85.7%	21	39.9%	14.6%	24.4%	90.6%
2006	23	26.2%	16.4%	9.2%	90.9%	23	37.7%	20.7%	7.1%	100.0%	22	35.9%	16.4%	14.7%	92.7%
2007	25	26.6%	15.0%	3.2%	80.0%	25	39.8%	20.7%	0.0%	100.0%	24	35.7%	15.8%	14.4%	87.3%
2008	39	30.6%	12.7%	5.2%	90.0%	38	41.8%	12.2%	12.5%	62.2%	38	35.7%	14.5%	12.4%	98.2%
2009	39	31.5%	16.2%	0.0%	100.0%	39	37.3%	15.2%	0.0%	59.9%	38	34.8%	13.3%	17.5%	91.1%
2010	40	29.3%	12.3%	4.5%	64.3%	40	41.3%	16.7%	10.3%	100.0%	39	33.9%	13.2%	17.0%	96.0%
2011	41	28.5%	15.6%	7.0%	100.0%	41	37.3%	16.1%	0.0%	100.0%	40	33.9%	13.1%	11.5%	91.0%
2012	33	28.5%	16.5%	0.0%	90.0%	32	36.0%	14.0%	9.1%	62.6%	33	29.8%	16.4%	0.0%	96.9%
Average		29.3%	15.2%	5.7%	89.4%		39.3%	16.7%	6.3%	83.8%		34.9%	14.7%	14.0%	93.0%

Table 1. Crime clustering for cities with at least 40,000 population, by five types of crime and total Part 1 crimes (continued)

	Motor vehicle theft					Larceny					Total crime				
Percent of crime in segments in top 5% of crime in current year (unadjusted concentration)															
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
2005	23	80.9%	20.3%	50.8%	100.0%	22	70.1%	13.4%	50.7%	100.0%	23	62.5%	13.7%	43.2%	100.0%
2006	25	77.6%	20.0%	45.8%	100.0%	25	67.8%	12.5%	48.4%	100.0%	25	58.8%	12.7%	40.0%	100.0%
2007	39	77.1%	18.2%	47.6%	100.0%	39	66.8%	10.6%	47.3%	100.0%	39	58.4%	10.5%	39.3%	100.0%
2008	39	78.0%	18.3%	50.3%	100.0%	38	66.4%	9.7%	45.3%	100.0%	39	58.8%	11.0%	38.6%	100.0%
2009	40	81.0%	18.2%	45.1%	100.0%	39	67.8%	9.8%	46.8%	100.0%	40	59.5%	10.9%	38.3%	100.0%
2010	41	81.1%	17.8%	47.9%	100.0%	40	67.7%	9.4%	47.4%	100.0%	41	59.5%	10.5%	39.1%	100.0%
2011	42	82.0%	18.7%	46.9%	100.0%	41	68.0%	9.0%	48.9%	100.0%	42	59.1%	10.4%	40.5%	100.0%
2012	33	81.3%	18.2%	49.6%	100.0%	33	71.1%	12.5%	49.0%	100.0%	34	61.9%	14.4%	41.2%	100.0%
Average		79.9%	18.7%	48.0%	100.0%		68.2%	10.9%	48.0%	100.0%		59.8%	11.7%	40.0%	100.0%
Percent of crime in segments in top 5% of crime over all years (historically adjusted concentration)															
2005	23	59.2%	15.7%	39.0%	100.0%	22	59.1%	12.0%	45.9%	100.0%	23	54.3%	12.7%	39.6%	100.0%
2006	25	59.3%	17.7%	32.2%	100.0%	25	59.7%	14.4%	40.5%	100.0%	25	53.4%	12.7%	35.6%	100.0%
2007	39	58.4%	13.5%	33.6%	100.0%	39	59.6%	11.7%	44.0%	100.0%	39	53.6%	10.7%	35.9%	100.0%
2008	39	59.3%	14.4%	34.6%	100.0%	38	58.5%	11.1%	36.4%	100.0%	39	54.0%	11.1%	33.2%	100.0%
2009	40	58.6%	13.9%	28.9%	100.0%	39	59.8%	11.0%	36.4%	100.0%	40	54.1%	10.8%	33.4%	100.0%
2010	41	57.2%	13.7%	31.1%	100.0%	40	59.7%	10.6%	36.7%	100.0%	41	53.9%	10.4%	33.7%	100.0%
2011	42	55.9%	16.6%	0.0%	100.0%	41	59.7%	10.3%	35.6%	100.0%	42	53.5%	10.8%	33.2%	100.0%
2012	33	56.9%	17.2%	20.6%	100.0%	33	56.0%	17.1%	0.0%	100.0%	34	51.5%	12.9%	16.1%	100.0%
Average		58.1%	15.3%	27.5%	100.0%		59.0%	12.3%	34.5%	100.0%		53.5%	11.5%	32.6%	100.0%
Percent of crime in segments in top 5% of crime in prior year (temporally adjusted concentration)															
2005	22	37.6%	17.5%	18.1%	100.0%	21	53.5%	12.6%	41.8%	97.0%	22	51.4%	13.1%	34.2%	97.6%
2006	23	36.9%	19.1%	9.0%	96.2%	23	46.7%	16.6%	0.0%	95.5%	23	47.0%	13.4%	32.4%	96.0%
2007	25	35.2%	15.2%	12.0%	78.6%	25	48.5%	15.3%	0.0%	92.8%	25	47.9%	12.5%	32.6%	93.2%
2008	39	37.1%	11.3%	16.8%	57.7%	38	50.9%	12.0%	27.9%	95.3%	39	48.7%	11.4%	27.6%	95.4%
2009	39	36.6%	15.5%	13.5%	100.0%	38	51.7%	12.4%	24.9%	95.1%	39	48.7%	11.5%	26.5%	96.1%
2010	40	34.6%	14.9%	8.2%	94.4%	39	51.3%	11.0%	28.7%	89.1%	40	48.9%	10.3%	30.7%	94.3%
2011	41	33.1%	15.9%	0.0%	95.8%	40	51.7%	11.8%	25.5%	95.3%	41	48.4%	10.8%	27.2%	96.9%
2012	33	29.7%	15.9%	0.0%	81.8%	33	51.9%	16.3%	14.3%	100.0%	34	45.1%	15.0%	0.0%	96.6%
Average		35.1%	15.7%	9.7%	88.1%		50.8%	13.5%	20.4%	95.0%		48.3%	12.3%	26.4%	95.8%

Table 2. Regression models predicting percent of crime events occurring in the top 5% of segments in a year for cities with at least 40,000 population, averaged results over 2005-12

	Aggravated assault		Robbery		Burglary		Motor vehicle theft		Larceny		Violent crime		Property crime		Total crime	
Model results using top 5% of segments in current year (unadjusted concentration)																
Crime events	-0.4873	**	-0.4731	**	-0.3748	**	-0.2793	**	-0.0559	**	-0.5326	**	-0.0510	**	-0.0481	**
	-(5.28)		-(7.21)		-(5.44)		-(5.02)		-(3.11)		-(8.15)		-(3.88)		-(4.21)	
Number of segments	0.0306	**	0.0185	**	0.0586	**	0.0462	**	0.0341	**	0.0512	**	0.0485	**	0.0497	**
	(3.95)		(5.82)		(3.93)		(3.16)		(2.81)		(6.07)		(3.34)		(3.67)	
Crime events X number of segments	0.0030	**	0.0041	**	0.0015	**	0.0008		-0.0003		0.0043	**	-0.0001		0.0000	
	(3.56)		(6.06)		(2.93)		(1.41)		-(1.04)		(7.52)		-(0.84)		(0.22)	
Intercept	0.9179	**	0.9658	**	0.7503	**	0.7841	**	0.6503	**	0.8618	**	0.5714	**	0.5638	**
	(42.97)		(105.66)		(21.01)		(18.85)		(21.56)		(37.96)		(18.81)		(20.08)	
R-square	0.544		0.747		0.527		0.508		0.340		0.719		0.396		0.425	
Average N	35.3		35.0		34.4		35.3		34.6		35.3		35.4		35.4	
Model results using top 5% of segments over all years (historically adjusted concentration)																
R-square	0.313		0.592		0.202		0.254		0.159		0.469		0.224		0.224	
Average N	35.3		35.0		34.4		35.3		34.6		35.3		35.4		35.4	
Model results using top 5% of segments from prior year (temporally adjusted concentration)																
R-square	0.043		0.049		0.074		0.062		0.113		0.036		0.172		0.182	
Average N	32.8		32.5		31.9		32.8		32.1		32.8		32.9		32.9	

Table 3. Cities with relatively low or high concentration of aggravated assault

			2010			Temporally adjusted in top 5% segments								Percent in top 5% segments (unadjusted)								Historically adjusted in top 5% segments							
	Population	Segments	Incidents	% in top 5	Expected % in top 5	2005	2006	2007	2008	2009	2010	2011	2012	2005	2006	2007	2008	2009	2010	2011	2012	2005	2006	2007	2008	2009	2010	2011	2012
Low concentration cities																													
Redondo Beach	66,054	1360	44	100%	100%	16%	18%	7%	16%	18%	7%	7%	9%	100%	100%	100%	100%	100%	100%	100%	100%	62%	44%	91%	56%	64%	52%	49%	51%
San Clemente	60,774	2206	23	100%	100%	35%	9%	3%	5%	23%	17%	11%	8%	100%	100%	100%	100%	100%	100%	100%	100%	76%	66%	68%	76%	82%	57%	63%	58%
Rancho Santa Margarita	47,539	1653	12	100%	100%	40%	24%	19%	15%	0%	8%	20%	0%	100%	100%	100%	100%	100%	100%	100%	100%	97%	82%	88%	77%	100%	100%	100%	100%
Aliso Viejo	46,329	1341	22	100%	100%	18%	19%	13%	18%	7%	5%	18%	29%	100%	100%	100%	100%	100%	100%	100%	100%	91%	85%	53%	91%	57%	73%	71%	67%
Irvine	199,117	5707	19	100%	100%	21%	19%	19%	21%	17%	32%	11%	.	100%	100%	100%	100%	100%	100%	100%	.	100%	100%	100%	100%	100%	100%	100%	.
Laguna Niguel	62,614	2373	25	100%	100%	33%	15%	36%	31%	16%	12%	15%	5%	100%	100%	100%	100%	100%	100%	100%	100%	80%	84%	89%	80%	84%	76%	88%	67%
Mission Viejo	92,615	3219	40	100%	100%	39%	22%	9%	24%	21%	20%	18%	11%	100%	100%	100%	100%	100%	100%	100%	100%	78%	75%	75%	84%	90%	66%	73%	69%
Corona	150,497	4951	81	100%	100%	27%	11%	24%	17%	23%	21%	27%	.	100%	100%	100%	100%	100%	100%	100%	.	70%	68%	67%	70%	79%	78%	55%	.
Colton	52,187	1564	56	100%	100%	.	.	.	.	.	14%	29%	26%	.	.	.	.	100%	100%	100%	100%	.	.	.	.	63%	70%	71%	69%
Perris	63,644	2081	45	100%	100%	30%	22%	30%	27%	21%	21%	14%	.	100%	91%	90%	97%	100%	100%	100%	.	52%	58%	53%	53%	60%	59%	60%	.
High concentration cities																													
Yorba Linda	62,915	2769	14	64%	100%	100%	91%	80%	90%	100%	64%	100%	90%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Escondido	140,998	4082	346	55%	64%	.	.	.	50%	54%	55%	58%	53%	.	.	100%	95%	96%	96%	98%	95%	.	.	70%	71%	73%	75%	73%	70%
Oceanside	164,709	5491	594	43%	51%	.	.	.	40%	44%	43%	44%	44%	.	.	97%	75%	82%	81%	79%	78%	.	.	58%	61%	64%	62%	60%	58%
San Diego	1,282,800	33924	3476	41%	54%	.	.	.	38%	41%	41%	41%	39%	.	.	97%	77%	78%	82%	85%	84%	.	.	57%	61%	60%	62%	61%	60%
Carlsbad	99,753	4549	153	39%	100%	.	.	.	35%	39%	39%	40%	37%	.	.	100%	100%	100%	100%	100%	100%	.	.	71%	75%	75%	74%	75%	73%
San Marcos	78,127	2238	117	43%	97%	.	.	.	36%	42%	43%	32%	35%	.	.	100%	94%	100%	100%	100%	100%	.	.	66%	66%	67%	69%	70%	74%
El Cajon	97,932	1940	264	40%	44%	.	.	.	32%	38%	40%	39%	35%	.	.	68%	66%	67%	70%	72%	95%	.	.	51%	58%	54%	57%	54%	54%
Vista	92,478	2458	214	37%	62%	.	.	.	41%	40%	37%	31%	31%	.	.	82%	69%	70%	81%	89%	100%	.	.	62%	61%	56%	52%	50%	59%
San Buenaventura (Ventura)	105,211	4376	116	31%	100%	31%	33%	40%	39%	44%	31%	32%	.	100%	100%	100%	100%	100%	100%	100%	.	68%	76%	72%	71%	71%	75%	74%	.
Encinitas	58,761	2371	85	40%	100%	.	.	.	32%	38%	40%	28%	38%	.	.	100%	99%	100%	100%	100%	100%	.	.	56%	70%	64%	63%	61%	70%

Table 4. Cities with relatively low or high concentration of burglary

		2010				Temporally adjusted in top 5% segments								Percent in top 5% segments (unadjusted)								Historically adjusted in top 5% segments							
	Population	Segments	Incidents	% in top 5	Expected % in top 5	2005	2006	2007	2008	2009	2010	2011	2012	2005	2006	2007	2008	2009	2010	2011	2012	2005	2006	2007	2008	2009	2010	2011	2012
Low concentration cities																													
Santa Monica	88,679	1815	329	52%	36%	.	.	19%	12%	18%	17%	11%	12%	.	43%	46%	47%	47%	52%	47%	44%	.	32%	30%	25%	30%	29%	26%	21%
La Mesa	56,250	1529	338	51%	33%	.	.	.	23%	20%	23%	24%	21%	.	.	54%	54%	53%	51%	60%	54%	.	.	40%	35%	32%	41%	42%	40%
Downey	110,921	2404	625	47%	31%	24%	29%	23%	22%	26%	19%	20%	19%	53%	58%	51%	51%	54%	47%	46%	50%	37%	41%	33%	34%	36%	29%	31%	25%
Los Angeles	3,772,486	73991	15928	54%	33%	28%	26%	24%	21%	22%	24%	21%	22%	56%	55%	54%	53%	53%	54%	54%	54%	38%	36%	37%	34%	36%	35%	34%	34%
Anaheim	333,039	7535	1401	64%	36%	.	.	.	32%	31%	34%	30%	0%	.	.	61%	62%	63%	64%	61%	100%	.	.	50%	48%	49%	51%	47%	100%
Redondo Beach	66,054	1360	394	53%	31%	24%	25%	22%	24%	30%	24%	26%	27%	50%	46%	41%	50%	50%	53%	48%	55%	41%	36%	30%	38%	43%	36%	34%	34%
Laguna Niguel	62,614	2373	108	100%	100%	32%	23%	14%	31%	28%	28%	30%	19%	100%	100%	100%	100%	100%	100%	100%	100%	43%	55%	50%	58%	49%	57%	48%	38%
Encinitas	58,761	2371	209	81%	62%	.	.	.	31%	26%	31%	27%	19%	.	.	67%	81%	72%	81%	80%	64%	.	.	46%	55%	49%	50%	47%	42%
Corona	150,497	4951	622	67%	46%	31%	34%	30%	25%	22%	25%	23%	.	63%	70%	71%	64%	68%	67%	66%	.	46%	48%	49%	42%	41%	42%	43%	.
San Clemente	60,774	2206	101	100%	99%	48%	21%	25%	22%	17%	20%	23%	45%	100%	100%	100%	100%	100%	100%	100%	100%	57%	62%	50%	61%	50%	50%	50%	57%
High concentration cities																													
Yorba Linda	62,915	2769	75	96%	100%	91%	93%	87%	98%	91%	96%	91%	97%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Temecula	95,829	3429	527	56%	39%	54%	59%	58%	67%	65%	56%	48%	.	86%	81%	87%	90%	89%	82%	83%	.	72%	69%	73%	76%	71%	65%	63%	.
Palm Desert	48,534	3027	562	46%	36%	51%	50%	47%	50%	47%	46%	47%	.	73%	73%	71%	72%	73%	75%	78%	.	61%	60%	61%	57%	57%	59%	65%	.
Lake Elsinore	48,644	2100	351	42%	39%	44%	42%	54%	40%	41%	42%	53%	.	78%	79%	85%	71%	71%	74%	80%	.	58%	60%	69%	58%	55%	60%	66%	.
Huntington Beach	188,914	6758	1803	47%	31%	.	35%	47%	47%	46%	47%	46%	46%	100%	65%	66%	69%	68%	67%	66%	65%	57%	54%	55%	58%	57%	57%	54%	54%
National City	57,343	1420	287	41%	34%	.	.	.	36%	38%	41%	54%	52%	.	.	61%	65%	67%	67%	76%	73%	.	.	50%	51%	55%	53%	65%	61%
Santee	52,966	1726	167	41%	56%	.	.	.	42%	45%	41%	43%	42%	.	.	75%	78%	82%	81%	82%	87%	.	.	54%	60%	59%	54%	62%	59%
Irvine	199,117	5707	766	46%	43%	50%	46%	52%	51%	50%	46%	42%	0%	73%	73%	79%	79%	79%	77%	74%	100%	59%	60%	66%	65%	66%	61%	58%	0%
Colton	52,187	1564	602	34%	28%	.	.	.	.	.	34%	39%	37%	.	.	.	.	64%	63%	57%	57%	.	.	.	.	46%	56%	51%	47%
Lake Forest	76,724	2481	167	40%	77%	34%	15%	38%	44%	42%	40%	42%	34%	100%	93%	95%	100%	97%	100%	100%	95%	41%	54%	60%	61%	59%	65%	62%	55%

Law of crime concentration

Table 5. Cities with relatively low or high concentration of total crime

		2010				Temporally adjusted in top 5% segments								Percent in top 5% segments (unadjusted)								Historically adjusted in top 5% segments							
	Population	Segments	Incidents	% in top 5	Expected % in top 5	2005	2006	2007	2008	2009	2010	2011	2012	2005	2006	2007	2008	2009	2010	2011	2012	2005	2006	2007	2008	2009	2010	2011	2012
Low concentration cities																													
Los Angeles	3,772,486	73991	72489	39%	18%	38%	37%	36%	28%	27%	31%	27%	31%	43%	43%	42%	39%	38%	39%	41%	41%	40%	39%	38%	33%	33%	34%	33%	34%
Redondo Beach	66,054	1360	1072	43%	19%	34%	32%	33%	31%	32%	33%	32%	28%	45%	42%	43%	44%	46%	43%	42%	43%	41%	36%	36%	38%	40%	36%	34%	33%
Santa Monica	88,679	1815	3301	42%	14%	.	.	34%	32%	33%	36%	35%	36%	.	40%	39%	39%	39%	42%	42%	42%	.	38%	37%	36%	37%	38%	38%	39%
Alhambra	83,389	1456	1868	49%	16%	39%	38%	38%	36%	35%	41%	40%	38%	44%	46%	45%	43%	43%	49%	46%	47%	42%	41%	41%	40%	39%	46%	41%	41%
Encinitas	58,761	2371	1005	53%	26%	.	.	.	39%	38%	38%	38%	40%	.	.	53%	55%	52%	53%	52%	52%	.	.	46%	47%	46%	45%	45%	44%
Santa Ana	325,216	5450	5119	44%	18%	44%	40%	40%	39%	36%	36%	38%	36%	49%	46%	47%	47%	44%	44%	46%	46%	46%	43%	43%	43%	41%	41%	41%	41%
Perris	63,644	2081	1688	51%	20%	44%	38%	39%	37%	41%	43%	40%	.	50%	47%	47%	47%	51%	51%	50%	.	46%	44%	43%	43%	46%	45%	45%	.
Anaheim	333,039	7535	6944	55%	18%	.	.	.	47%	46%	49%	47%	16%	.	.	56%	53%	55%	55%	54%	100%	.	.	53%	50%	52%	53%	51%	16%
Fontana	189,466	5354	3648	56%	20%	.	.	38%	41%	43%	45%	44%	40%	.	53%	49%	50%	51%	56%	54%	54%	.	47%	45%	46%	47%	50%	48%	44%
San Clemente	60,774	2206	525	63%	32%	62%	40%	34%	41%	42%	38%	40%	41%	78%	62%	61%	63%	63%	63%	63%	66%	63%	51%	46%	53%	49%	51%	48%	53%
High concentration cities																													
Yorba Linda	62,915	2769	211	94%	70%	98%	96%	93%	95%	96%	94%	97%	97%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Temecula	95,829	3429	2314	61%	20%	66%	64%	62%	64%	66%	61%	59%	.	74%	72%	72%	74%	74%	70%	71%	.	70%	68%	67%	70%	70%	65%	66%	.
Palm Desert	48,534	3027	1775	61%	21%	63%	61%	58%	61%	60%	61%	61%	.	70%	69%	66%	70%	71%	72%	72%	.	66%	65%	63%	65%	65%	66%	66%	.
Escondido	140,998	4082	4451	56%	17%	.	.	.	59%	54%	56%	59%	61%	.	.	62%	64%	60%	62%	65%	66%	.	.	60%	61%	57%	59%	62%	63%
National City	57,343	1420	1952	54%	16%	.	.	.	54%	58%	54%	58%	56%	.	.	54%	58%	62%	59%	62%	61%	.	.	53%	56%	60%	56%	60%	60%
Chula Vista	229,614	5995	5079	53%	19%	.	.	.	58%	56%	53%	58%	55%	.	.	65%	62%	62%	60%	64%	62%	.	.	63%	60%	59%	57%	61%	60%
San Marcos	78,127	2238	1694	56%	20%	.	.	.	55%	55%	56%	50%	54%	.	.	59%	63%	64%	63%	59%	62%	.	.	55%	59%	59%	60%	55%	57%
Downey	110,921	2404	3946	58%	14%	51%	57%	53%	51%	57%	58%	53%	50%	58%	61%	59%	58%	63%	62%	56%	57%	56%	59%	56%	55%	60%	60%	55%	54%
Mission Viejo	92,615	3219	1172	54%	29%	54%	45%	53%	57%	55%	54%	53%	53%	72%	66%	68%	71%	70%	69%	72%	69%	54%	58%	61%	64%	60%	60%	63%	60%
Vista	92,478	2458	2333	53%	18%	.	.	.	50%	54%	53%	52%	55%	.	.	56%	56%	59%	60%	58%	61%	.	.	54%	54%	57%	56%	55%	57%

Law of crime concentration

Table 6. Large Cities (> 100,000 population) for total crime

			2010			Temporally adjusted in top 5% segments								Percent in top 5% segments (unadjusted)								Historically adjusted in top 5% segments							
	Population	Segments	Incidents	% in top 5	Expected % in top 5	2005	2006	2007	2008	2009	2010	2011	2012	2005	2006	2007	2008	2009	2010	2011	2012	2005	2006	2007	2008	2009	2010	2011	2012
Irvine	199,117	5707	19	100%	100%	28%	17%	14%	15%	14%	38%	11%	.	100%	100%	100%	100%	100%	100%	100%	.	100%	100%	100%	100%	100%	100%	100%	.
Corona	150,497	4951	81	100%	100%	28%	14%	26%	15%	26%	21%	26%	.	100%	100%	100%	100%	100%	100%	100%	.	68%	68%	67%	72%	75%	74%	70%	.
Burbank	102,723	2195	73	100%	100%	34%	27%	23%	24%	17%	25%	12%	21%	100%	100%	100%	100%	100%	100%	100%	100%	59%	59%	61%	56%	61%	55%	56%	46%
Anaheim	333,039	7535	325	100%	100%	.	.	.	29%	31%	28%	31%	0%	.	.	100%	100%	100%	100%	100%	100%	.	.	67%	63%	67%	69%	65%	0%
Fontana	189,466	5354	240	100%	100%	.	.	6%	26%	29%	26%	31%	26%	.	100%	100%	100%	100%	100%	100%	100%	.	56%	56%	62%	58%	62%	62%	63%
Huntington Beach	188,914	6758	122	100%	100%	.	10%	26%	26%	34%	17%	32%	30%	100%	100%	100%	100%	100%	100%	100%	100%	64%	75%	69%	77%	73%	67%	82%	73%
Santa Ana	325,216	5450	431	77%	69%	29%	26%	31%	28%	24%	24%	24%	25%	76%	73%	83%	86%	85%	77%	87%	91%	44%	44%	49%	48%	47%	45%	47%	50%
Downey	110,921	2404	130	100%	96%	21%	26%	22%	29%	26%	28%	33%	39%	100%	100%	92%	100%	100%	100%	100%	100%	54%	55%	52%	50%	53%	60%	58%	59%
Moreno Valley	187,428	5316	251	94%	100%	28%	26%	33%	29%	31%	24%	33%	.	96%	93%	90%	90%	94%	94%	96%	.	54%	52%	55%	54%	54%	48%	53%	.
Los Angeles	3,772,486	73991	7686	79%	53%	35%	33%	32%	30%	31%	33%	30%	34%	68%	69%	70%	74%	75%	79%	85%	87%	49%	51%	49%	52%	51%	50%	53%	52%
Riverside	300,553	9132	586	91%	80%	32%	34%	34%	32%	31%	33%	30%	34%	75%	80%	80%	85%	93%	91%	94%	93%	49%	54%	52%	52%	53%	53%	54%	57%
Chula Vista	229,614	5995	187	100%	100%	.	.	.	39%	32%	31%	37%	31%	.	.	100%	100%	100%	100%	100%	100%	.	.	75%	77%	71%	69%	80%	71%
San Buenaventura (Ventura)	105,211	4376	116	100%	100%	31%	33%	38%	39%	43%	31%	34%	.	100%	100%	100%	100%	100%	100%	100%	.	70%	76%	72%	71%	71%	77%	74%	.
San Diego	1,282,800	33924	3476	82%	54%	.	.	.	38%	42%	41%	41%	39%	.	.	97%	77%	78%	82%	85%	84%	.	.	58%	61%	60%	62%	60%	60%
Oceanside	164,709	5491	594	81%	52%	.	.	.	40%	41%	44%	43%	44%	.	.	97%	75%	82%	81%	79%	78%	.	.	58%	60%	64%	61%	61%	58%
Escondido	140,998	4082	346	96%	64%	.	.	.	50%	54%	54%	58%	53%	.	.	100%	95%	96%	96%	98%	95%	.	.	71%	71%	73%	75%	73%	71%

Law of crime concentration
Figure 1

City A

n	n	n	n	n
n	n	n	n	n
n	n	**X**	n	n
n	n	n	n	n

City B

n	n	n	n	n
n	**X**	**X**	**X**	n
n	**X**	**X**	**X**	n
n	n	n	n	n

Note: X = high crime; n = low crime

Appendix

Table A1. Summary statistics for the cities in the analyses (based on various population thresholds)

	Cities with population at least 40,000				Cities with population at least 10,000				Cities with population at least 100,000			
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
% aged 15 to 29	22.1	3.4	12.8	28.4	22.1	6.8	0.6	77.6	23.7	2.6	19.1	28.4
Avg HH income	83,182	24,804	45,586	155,671	86,421	34,522	42,917	236,370	77,339	14,502	46,482	113,185
Avg home value	168,376	77,283	63,203	414,558	175,470	95,005	51,557	486,417	151,481	59,818	79,784	275,861
% Poverty	11.7	5.9	2.3	28.7	11.3	6.3	1.6	30.1	13.3	4.7	7.0	24.1
% Black	5.3	6.5	0.1	32.9	5.3	9.9	0.0	87.0	5.5	5.3	0.2	18.6
% Asian	13.6	14.7	0.2	63.1	10.7	13.4	0.0	63.1	10.2	7.5	0.8	38.1
% Latino	41.5	25.0	9.0	97.8	40.3	26.6	2.7	98.5	47.0	21.2	9.0	97.8
Ethnic heterogeneity	51.9	13.9	4.4	71.7	48.2	15.3	3.0	73.5	56.1	14.2	4.4	69.8
% with bachelor's	28.8	16.4	3.8	65.5	27.8	17.7	3.4	73.8	25.3	13.1	5.4	65.5
Avg length of residence	9.9	2.6	5.3	15.8	10.4	2.8	1.4	18.9	9.0	1.8	6.6	13.4
Population	174,496	480,990	40,075	3,772,486	90,095	329,683	10,104	3,772,486	403,813	811,240	102,723	3,772,486
% Unemployed	9.0	2.4	4.8	16.4	9.6	3.6	4.8	32.8	9.9	1.8	6.7	13.0
N	42				82				16			

Table A2. Crime counts for cities in analyses

Year		Agg. assault	Robbery	Burglary	M.V. theft	Larceny	Violent	Property
2005	Mean	281.2	155.0	416.0	459.1	993.1	443.3	1866.7
	S.D.	1192.1	966.8	1841.6	2167.4	4931.8	2191.7	8919.7
	Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Max	12538.6	10317.1	19541.7	22850.4	52448.9	23277.2	94841.0
2006	Mean	279.3	174.2	432.6	447.0	988.4	460.3	1866.4
	S.D.	1109.1	1050.5	1724.8	2003.7	4607.9	2189.8	8313.4
	Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Max	11613.2	11208.6	18161.2	21177.3	49033.8	23246.5	88372.3
2007	Mean	255.5	165.1	467.4	494.2	1135.4	425.9	2095.9
	S.D.	928.5	891.0	1642.6	1990.9	4554.1	1839.4	8146.8
	Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Max	10578.1	10506.8	18072.7	20060.1	49800.6	21455.3	87933.3
2008	Mean	270.0	165.9	470.3	447.0	962.2	441.1	1878.3
	S.D.	966.6	937.4	1694.1	1871.5	2995.0	1916.1	6493.9
	Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Max	10641.4	11074.6	18694.3	19928.4	28521.3	22078.5	67144.0
2009	Mean	239.3	151.1	427.8	354.7	885.0	394.6	1666.5
	S.D.	821.8	833.7	1527.0	1470.0	2684.7	1657.6	5629.6
	Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Max	8838.2	9836.6	16963.0	15941.7	26686.0	18952.4	59590.6
2010	Mean	225.0	132.6	412.8	326.2	865.5	361.3	1603.1
	S.D.	735.3	745.0	1447.7	1347.9	2571.1	1479.0	5316.2
	Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Max	7801.8	8808.2	16098.0	14792.5	25532.2	16875.6	56422.6
2011	Mean	187.7	118.5	397.3	302.2	817.4	309.5	1515.8
	S.D.	683.5	698.8	1458.4	1288.8	2501.2	1390.0	5178.8
	Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Max	7490.8	8278.0	16415.8	14075.5	24184.1	16038.0	54675.3
2012	Mean	193.4	115.0	357.9	307.9	764.5	312.3	1430.0
	S.D.	694.0	664.5	1467.7	1342.0	2751.8	1366.5	5499.7
	Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Max	7056.7	7424.5	15580.4	13578.6	25079.1	14758.5	54238.2

Table A3. Crime clustering for cities, by five types of crime. Using all cities with at least 10,000 population

	Aggravated assault					Robbery					Burglary				
Percent of crime in segments in top 5% of crime in current year (unadjusted concentration)															
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
2005	39	96.5%	9.0%	65.7%	100.0%	36	97.5%	7.7%	69.2%	100.0%	39	80.9%	18.5%	44.4%	100.0%
2006	43	95.0%	10.5%	62.3%	100.0%	40	96.2%	9.3%	66.0%	100.0%	42	75.6%	19.1%	43.1%	100.0%
2007	74	94.3%	11.3%	54.5%	100.0%	71	96.8%	8.0%	65.3%	100.0%	73	73.6%	17.0%	41.3%	100.0%
2008	75	93.2%	12.2%	52.1%	100.0%	67	96.9%	8.0%	67.5%	100.0%	73	74.9%	17.4%	45.5%	100.0%
2009	75	94.4%	11.5%	47.6%	100.0%	71	97.3%	7.2%	64.4%	100.0%	74	75.0%	17.0%	46.7%	100.0%
2010	77	94.8%	10.1%	63.9%	100.0%	71	98.3%	6.0%	67.2%	100.0%	76	73.7%	16.9%	43.1%	100.0%
2011	79	95.5%	10.0%	55.8%	100.0%	75	98.9%	4.0%	76.8%	100.0%	76	73.4%	17.1%	46.2%	100.0%
2012	59	97.2%	7.2%	67.4%	100.0%	57	99.1%	3.3%	83.3%	100.0%	61	74.3%	19.1%	44.1%	100.0%
Average		95.1%	10.2%	58.7%	100.0%		97.6%	6.7%	70.0%	100.0%		75.2%	17.8%	44.3%	100.0%
Percent of crime in segments in top 5% of crime over all years (historically adjusted concentration)															
2005	39	71.2%	19.5%	41.2%	100.0%	36	87.2%	17.1%	51.0%	100.0%	39	52.4%	15.2%	22.2%	100.0%
2006	43	70.3%	20.2%	41.3%	100.0%	40	87.3%	16.5%	50.2%	100.0%	42	54.3%	17.8%	24.3%	100.0%
2007	74	68.6%	17.9%	26.3%	100.0%	71	85.8%	16.4%	48.9%	100.0%	73	52.5%	14.8%	8.6%	100.0%
2008	75	69.1%	17.3%	33.7%	100.0%	67	84.5%	16.7%	46.2%	100.0%	73	52.8%	14.6%	25.0%	100.0%
2009	75	69.3%	17.9%	33.3%	100.0%	71	85.7%	16.6%	49.5%	100.0%	74	51.1%	14.9%	10.7%	100.0%
2010	77	68.7%	18.8%	37.5%	100.0%	71	85.7%	16.6%	41.2%	100.0%	76	50.7%	15.1%	24.1%	100.0%
2011	79	70.4%	18.7%	30.8%	100.0%	75	85.1%	17.7%	35.4%	100.0%	76	49.4%	14.9%	13.3%	100.0%
2012	59	65.9%	18.6%	0.0%	100.0%	57	86.4%	16.1%	50.9%	100.0%	61	47.9%	18.5%	0.0%	100.0%
Average		69.2%	18.6%	30.5%	100.0%		86.0%	16.7%	46.7%	100.0%		51.4%	15.7%	16.0%	100.0%
Percent of crime in segments in top 5% of crime in prior year (temporally adjusted concentration)															
2005	38	28.9%	16.3%	0.0%	100.0%	35	35.9%	20.8%	0.0%	85.7%	38	40.6%	17.0%	11.1%	100.0%
2006	41	21.0%	15.5%	0.0%	90.9%	38	32.7%	23.6%	0.0%	100.0%	40	33.4%	18.8%	0.0%	100.0%
2007	42	21.7%	15.9%	0.0%	80.0%	40	40.3%	24.3%	0.0%	100.0%	42	31.6%	15.5%	0.0%	87.3%
2008	75	28.8%	17.5%	0.0%	100.0%	67	38.0%	17.8%	0.0%	83.7%	73	32.4%	14.2%	0.0%	98.2%
2009	74	29.9%	17.3%	0.0%	100.0%	70	35.0%	18.4%	0.0%	72.7%	73	32.4%	12.3%	0.0%	91.1%
2010	76	26.8%	14.5%	0.0%	64.3%	70	39.5%	19.9%	0.0%	100.0%	74	30.3%	13.1%	0.0%	96.0%
2011	78	27.3%	18.6%	0.0%	100.0%	74	35.0%	20.3%	0.0%	100.0%	75	31.3%	15.4%	0.0%	100.0%
2012	59	26.7%	18.2%	0.0%	90.0%	57	32.4%	18.5%	0.0%	83.3%	60	26.4%	15.2%	0.0%	96.9%
Average		26.4%	16.7%	0.0%	90.6%		36.1%	20.4%	0.0%	90.7%		32.3%	15.2%	1.4%	96.2%

Table A3. Crime clustering for cities, by five types of crime. Using all cities with at least 10,000 population (continued)

	Motor vehicle theft					Larceny					Total crime				
Percent of crime in segments in top 5% of crime in current year (unadjusted concentration)															
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
2005	42	85.2%	18.9%	50.8%	100.0%	42	73.3%	15.7%	50.7%	100.0%	43	66.3%	16.8%	43.2%	100.0%
2006	43	82.4%	19.4%	45.8%	100.0%	46	70.7%	15.9%	45.1%	100.0%	47	63.9%	18.7%	37.8%	100.0%
2007	73	79.6%	18.4%	40.5%	100.0%	76	67.2%	13.8%	39.6%	100.0%	77	60.3%	14.5%	34.4%	100.0%
2008	75	82.3%	18.4%	41.8%	100.0%	78	68.0%	14.1%	41.1%	100.0%	79	61.0%	15.0%	33.4%	100.0%
2009	75	85.1%	18.0%	42.0%	100.0%	77	68.7%	13.2%	41.8%	100.0%	78	60.7%	14.1%	34.3%	100.0%
2010	76	84.5%	17.8%	44.5%	100.0%	78	68.5%	12.5%	38.5%	100.0%	79	60.4%	14.0%	35.0%	100.0%
2011	77	85.4%	17.7%	46.9%	100.0%	79	68.0%	13.0%	44.4%	100.0%	80	60.2%	13.8%	34.5%	100.0%
2012	62	85.9%	17.2%	47.5%	100.0%	62	69.9%	13.3%	46.0%	100.0%	63	61.6%	14.9%	35.9%	100.0%
Average		83.8%	18.2%	45.0%	100.0%		69.3%	13.9%	43.4%	100.0%		61.8%	15.2%	36.1%	100.0%
Percent of crime in segments in top 5% of crime over all years (historically adjusted concentration)															
2005	42	60.3%	21.9%	0.0%	100.0%	42	59.1%	16.5%	30.1%	100.0%	43	55.8%	16.8%	31.4%	100.0%
2006	43	61.5%	18.5%	32.2%	100.0%	46	61.4%	18.7%	22.5%	100.0%	47	57.3%	19.0%	25.2%	100.0%
2007	73	59.7%	15.7%	31.8%	100.0%	76	57.6%	15.7%	20.3%	100.0%	77	54.4%	15.3%	22.2%	100.0%
2008	75	61.1%	16.4%	31.8%	100.0%	78	59.0%	16.5%	23.2%	100.0%	79	55.2%	16.8%	17.3%	100.0%
2009	75	59.2%	16.4%	20.0%	100.0%	77	59.3%	15.1%	27.5%	100.0%	78	54.5%	15.5%	20.1%	100.0%
2010	76	58.3%	15.9%	27.9%	100.0%	78	58.9%	15.2%	20.7%	100.0%	79	53.9%	15.2%	23.3%	100.0%
2011	77	58.7%	17.7%	0.0%	100.0%	79	57.9%	15.2%	18.4%	100.0%	80	53.4%	15.5%	18.0%	100.0%
2012	62	60.6%	18.9%	20.6%	100.0%	62	56.0%	16.8%	0.0%	100.0%	63	51.5%	15.0%	16.1%	100.0%
Average		59.9%	17.7%	20.5%	100.0%		58.6%	16.2%	20.3%	100.0%		54.5%	16.1%	21.7%	100.0%
Percent of crime in segments in top 5% of crime in prior year (temporally adjusted concentration)															
2005	41	31.4%	18.1%	0.0%	100.0%	41	48.9%	17.0%	0.0%	100.0%	42	47.8%	15.8%	0.0%	97.6%
2006	40	32.6%	18.0%	0.0%	96.2%	43	44.0%	18.3%	0.0%	95.5%	43	43.6%	16.2%	0.0%	96.0%
2007	41	31.2%	14.5%	0.0%	78.6%	44	45.0%	16.1%	0.0%	92.8%	45	44.0%	14.9%	0.0%	93.2%
2008	75	34.8%	13.0%	0.0%	68.0%	76	45.4%	14.6%	0.0%	95.3%	77	44.8%	14.3%	0.0%	95.4%
2009	74	35.7%	17.3%	0.0%	100.0%	76	46.5%	16.0%	0.0%	95.1%	77	46.1%	15.2%	0.0%	100.0%
2010	75	31.4%	16.9%	0.0%	100.0%	76	47.8%	14.5%	12.1%	100.0%	77	46.5%	14.4%	5.8%	100.0%
2011	76	31.1%	16.7%	0.0%	95.8%	78	46.8%	14.9%	11.5%	100.0%	79	44.9%	13.8%	0.0%	96.9%
2012	61	28.2%	15.4%	0.0%	81.8%	61	46.7%	17.2%	5.7%	100.0%	62	43.1%	14.6%	0.0%	96.6%
Average		32.1%	16.2%	0.0%	90.1%		46.4%	16.1%	3.7%	97.3%		45.1%	14.9%	0.7%	96.9%

Table A4. The 42 cities with at least 40,000 population

Alhambra
Aliso Viejo
Anaheim
Baldwin Park
Burbank
Carlsbad
Chula Vista
Colton
Corona
Downey
El Cajon
Encinitas
Escondido
Fontana
Huntington Beach
Irvine
La Mesa
Laguna Niguel
Lake Elsinore
Lake Forest
Los Angeles
Mission Viejo
Montebello
Moreno Valley
National City
Oceanside
Palm Desert
Perris
Poway
Rancho Santa Margarita
Redondo Beach
Riverside
San Buenaventura (Ventura)
San Clemente
San Diego
San Marcos
Santa Ana
Santa Monica
Santee
Temecula
Vista
Yorba Linda