EXAMINING THE "LAW OF CRIME CONCENTRATIONS" ACROSS MULTIPLE JURISDICTIONS

by

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A Dissertation
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of
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DEDICATION

This is dedicated to my loving wife Eun Kyung, my three wonderful children Daniel, Jua, and Aiden.

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I would like to thank Cynthia Lum, Christopher Koper, Charlotte Gill, and Julie Hibdon who have made this happen. I also thank David Weisburd whose work inspired me to think about the issues addressed in the paper.

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United Kingdom...UK

ABSTRACT

EXAMINING THE "LAW OF CRIME CONCENTRATIONS" ACROSS MULTIPLE JURISDICTIONS

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Research has repeatedly shown that crime is concentrated at relatively smaller places. Weisburd (2015) argues that this may indicate the existence of a "law of crime concentration." However, theoretical and empirical work in this area (i.e. social disorganization, routine activity, environmental criminology) has found a variety of factors that contribute to crime concentrations at places, which if variable, may also contribute to the variability of crime concentration at places. This study examines the salience of Weisburd's law of crime concentration by similarly calculating crime concentration across all 43 police jurisdictions in England and Wales. The analysis confirms that crime indeed concentrates in a small proportion of street segments. However, this study also finds that the level of crime concentration can vary by crime types and at different thresholds of crime across jurisdictions. Further, two specific aspects of small places—population density and the length of street segments—

significantly explains the variation of these concentrations. The results expand understanding of the concentration of crime at place to test the law of crime concentration.

CHAPTER ONE: INTRODUCTION

Criminologists have often focused their research efforts on studying individuals, trying to understand why people commit crime and how they can be reformed. However, others have emphasized that places and their characteristics are also important in understanding crime and crime prevention. This line of theorizing was evident in the work of early social disorganization scholars such as Shaw and McKay (1929) who described patterns of crime emerging from geographic patterns of invasion and succession of different socioeconomic and demographic groups. Later, scholars working in areas of environmental criminology or crime pattern theory (see Brantingham & Brantingham, 1991) have argued that features of the built and social environment create "templates" or "activity backcloths" (Brantingham & Brantingham, 1993) that when combined with offender "readiness" can provide a fertile location for crime to occur. Similarly, those who advocate for a criminology of places (see Eck & Weisburd, 1995; Sherman, Gartin, & Buerger, 1989; Weisburd et al., 2012) have tried to link routine activities and opportunity structures to geographic crime patterns, especially for purposes of crime prevention. For example, Sherman et al. (1989) drew from both theories of routine activities (Cohen & Felson, 1979) and environmental criminology (Brantingham & Brantingham, 1981, 1993) to hypothesize that crime was attracted or generated at specific places because of the opportunities at those places created by converging routine and environmental contexts.

These place-based approaches to criminology are theoretically and empirically rich and wide-ranging, but all are connected by the belief that crime geographically concentrates. Since Sherman et al. (1989), criminologists in both the environmental criminology and crime and place traditions have continued to build strong empirical support for the existence of crime concentrations (see Eck, Clarke, & Guerette, 2007; Groff, Weisburd, & Morris, 2009; Groff, Weisburd, & Yang, 2010; Johnson & Bowers, 2004; Madensen & Eck, 2008; Smith, Frazee, & Davison, 2000; Weisburd et al., 2012; Wikström et al., 2012). There is also a growing evaluation literature that finds that when criminal justice agents (for example the police) target these crime concentrations, they can reduce and prevent crime (e.g. Braga & Bond, 2008; Braga et al., 1999, 2014; Groff et al., 2015; Lum & Koper, 2017; National Research Council, 2004; National Academy of Sciences, 2017; Ratcliffe et al., 2011; Sherman & Weisburd, 1995; Taylor, Koper, & Woods, 2011; Telep et al., 2014; Weisburd & Eck, 2004; Weisburd & Green, 1995). These findings have led Weisburd (2015) to assert that there is a "Law of Crime Concentration," noting that studies seem to show, again and again, that crime tends to concentrate "within a narrow bandwidth of percentages for a defined cumulative proportion of crime" (p. 132).

Can such a law exist? Weisburd argues that research consistently seems to show that a large proportion of crime is concentrated in a small proportion of places, especially microgeographic places (i.e. street addresses and street segments) (see Pierce et al., 1988;

Sherman et al., 1989; Weisburd & Amram, 2015; Weisburd & Green, 1995; Weisburd et al., 2004, 2009, 2012; Wheeler et al., 2015). While most of these calculations are conducted in large urban cities, a few have also focused on suburban areas or smaller towns (e.g. Dario et al., 2015; Hibdon, 2013; Gill, Wooditch, & Weisburd, 2017). To make his point, Weisburd (2015) examined crime concentrations in eight cities of varying size and urbanity. He defines large cities as places with populations ranging from approximately 300,000 to more than 8,000,000 people, and small cities as places with populations ranging from approximately 70,000 to 108,000 people. To calculate crime concentration across these cities, he uses the same type of data (crime incidents), the same measure of crime (incident types), the same microgeographic unit of analysis (street segment), and the same time frame (one year). He found that when examining street segments in reverse ranking from the most to the least crime in those street segments, about 50% of crime was concentrated in just 4.2% to 6% of the streets in the larger cities. He also confirmed the preliminary finding by Hibdon (2013) that crime might be even more concentrated in less populated cities; between 2.1% and 3.5% of street segments produce 50% of crime at street segments.

Weisburd (2015) concedes that his study only includes a small sample of cities, many of which are places in which he or colleagues have researched. However, his assertion of a universal law is intriguing. For example, it appears to be more specific than the well-known Tobler's (1970) First Law of Geography, which states more generally that "everything is related to everything, but near things are more related than distant things" (p. 36). However, theories and studies focused on environmental criminology, routine activities, and place-based criminology also suggest that there are many factors that can influence where crime events occur and therefore may also influence the levels and patterns of concentration at certain places. Also, previous studies about the nature of crime concentrations show different levels of crime concentrations across places (see, Hipp & Kim, 2017; Weisburd, 2015). This study examines, therefore, whether such a law hold true across a variety of places with differing social and physical characteristics at places. For example, if we examined all jurisdictions in an entire country, would the law hold? Crime concentration may be influenced by the size of the jurisdiction, its population density, the number of police officers, urbanization, the spatial unit of analysis (for example, street segments), and other factors. Furthermore, crime concentrations may differ depending on what types of crime are examined. And, if variations are found in the concentration of crime, what might be the reasons for such variation in crime concentrations across places?

To date, only one study—Hipp and Kim (2016)—has tested Weisburd's law across multiple jurisdictions. They examined crime concentrations in 42 cities in Southern California, finding variations of crime concentrations. In particular, they question the derivation of the calculation of crime concentration itself, suggesting that crime concentrations may not only vary, but vary when different methods are used to calculate them. They conclude that their findings "open an exciting new area of research exploring why levels of crime concentration may vary over cities" (p. 595).

To further test the salience of Weisburd's law of concentration, this study does not select certain places within a larger political unit. Rather, this study examines crime concentrations across all jurisdictions in an entire political jurisdiction. Specifically, this study calculates crime concentrations for all 43 police force jurisdictions in England and Wales at the street segment level to determine if variations in a jurisdiction-level calculation of crime concentrations exist, and if the law of crime concentration holds true outside of the United States (i.e. UK). Further, following Hipp and Kim's suggestions and adding to this literature, characteristics of these jurisdictions will be examined against calculated crime concentrations to understand whether such characteristics can explain variations.

CHAPTER TWO: LITERATURE REVIEW

The notion that crime geographically concentrates has been supported across a variety of modern criminological theories. However, these theories differ as to the nature and explanation of geographic crime patterns. These theories generally can be described as those focused more on macro- (or meso-) geographic levels (such as cities, neighborhoods, and communities) or micro-geographic levels, such as street segments, addresses, or other very small places.

Theories of Crime Concentration at the Macro- and Meso-Geographic Levels

The study of geographic crime patterns dates back to the early 1900s. The most notable early work was that of the Chicago School of social disorganization. Burgess (1925) divided Chicago into five zones (central business district, transitional zone, working class zone, residential zone, and commuter zone) to understand the spatial patterns of human activity within an urban environment. He hypothesized that people in each zone continue to move to the outer zones because of the influx of immigrants and workers to the inner zone, which also was where businesses and manufacturing companies were located. Transitional zones, which saw the most movement of people and residential instability was also the places where high juvenile delinquency and gang activities seemed to concentrate.

Building on Burgess's work, Shaw et al. (1929) gathered empirical evidence to see whether patterns of juvenile delinquency differed in those five zones as proposed by Burgess. They hand-mapped delinquents from 140 neighborhoods using data from juvenile court records from 1900 to 1930 and found that neighborhoods within the zones of transition indeed had the highest concentrations of delinquents compare to other zones. They identified a number of social forces that characterized the zones of transition, and in particular focused on high levels of residential instability that marked these places. These areas were also places where residents had low socioeconomic status, were racially and ethnically heterogeneous, and had higher levels of family disruption. Shaw and McKay (1942) argued all of this led to a consistent concentration (and "subculture") of juvenile delinquents (and of crime) in these places. Kornhauser (1978) later articulated that such conditions produced low levels of informal social control which mediated these forces and delinquency (see also Sampson & Groves, 1989).

Most recently, Sampson has examined a more "meso" geographic unit—the community (or neighborhood)—in trying to explain why crime occurs in certain communities more than others. Building on the social disorganization theorists' ideas of informal social control, Sampson and colleagues (see Sampson & Groves, 1989; Sampson et al., 1997; Sampson & Raudenbush, 2001; Sampson, 2011) argued that community members social ties and participation in collective activities, combined with their "willingness to intervene on behalf of the common good" (Sampson et al., 1997, p 918)—"collective efficacy" as coined by Sampson, could explain varying crime rates across communities. Sampson et al. (2002) reviewed forty studies and found that certain neighborhood effects, such as neighborhood ties, social control, mutual trust, institutional resources, disorder, and routine activity patterns, explain variations in crime rates.

The evolution, criticisms, and tests of social disorganization theory have been well-documented by others are not regurgitated here (see Bursik, 1988; Sampson, 1987; Sampson & Groves, 1989; Vold & Bernard, 1986). However it is important to note that although some of this work did and does focus on individuals and their offending patterns, these macro theories also emphasized the importance of how crime might distribute (or concentrate) across places.

Theories That Questioned the Macro-Geographic Explanations of Crime Patterns

One critique of social disorganization relevant to this study was that offered by Sherman, Gartin, and Buerger (1989). They argued that sociological conceptualizations of place (e.g. socioeconomic status and human behavior) were unclear, while physical boundaries of human life might be determined by fixed physical environments (i.e. river, major roadways, land use, etc.). For example, some urban downtown areas have high crime, but not all residents are poor or in economic transition. Housing markets also produce very different geographical distributions of crime in American cities (Weisburd et al., 2012). Consequently, cities and also neighborhoods within them may be very diverse and not easily generalized with regard to crime patterns. Sherman et al. (1989) and also Weisburd et al. (2012) have argued that macro-geographic theories might be inadequate in explaining the variability of crime patterns within places that seem generally crime-ridden.

Other criminological theories have tried to explain crime patterns at more specific places. One theory that challenged the social disorganization explanations of crime was routine activities theory (Cohen & Felson, 1979). Cohen and Felson questioned why crime rates had increased between 1960 and 1975 even though social and economic conditions had improved since 1960 (i.e. higher education, lower unemployment rate, increased the medium family income, and lower poverty level (1979:588). Cohen and Felson (1979) hypothesized that rather than more macro, socio-economic forces that impacted subcultures of informal control, it was that macro forces of modernization impacted routine activities of everyday life, which in turn influenced criminal opportunity and crime rates. In particular, the occurrence of crime depends on the convergence in space and time of likely offenders, suitable targets, and the absence of capable guardians within their routine activities. Unlike social disorganization theory, routine activities approaches attempted to account for crime events at a specific place where offenders, targets, and guardians interact in terms of their everyday rhythms (how regular), tempos (how often), and timing (when) under specific social and physical settings (Cohen & Felson, 1979).

A major contribution to understanding geographic crime patterns came from environmental criminologists, such as Paul and Patricia Brantingham (see Brantingham & Brantingham, 1991, 1993). Their “crime pattern theory” focuses on the specific environmental contexts that can influence the occurrence of criminal activities at any given location. Brantingham and Brantingham (1993) hypothesized that individuals are tied to more specific social-geographic and physical structures of an area, which results in unequal geographic crime distributions. In particular, they emphasize the existence of "templates," "backcloths," and activity spaces that provided the fertile geographic and temporal grounds for specific crime events to occur at certain places. Although the environmental backcloth includes multiple factors influencing offenders' criminal activities, offenders may select certain places with high criminal opportunities during their non-criminal activities (Brantingham & Brantingham, 1981), leading to an overlap between places in which offenders might conduct both legitimate and illegitimate activities. In particular, Brantingham and Brantingham (1993) argued that crime occurs at specific places, such as near central nodes and at pathways that offenders know well through their routines or previous experiences. They define such places as "crime generators," which are specific sites or land uses or locales where people gather (i.e. shopping malls, entertainment districts, office districts, and large housing complexes or estates), or "crime attractors," which are particular places, areas, neighborhoods, districts which create well known criminal opportunities for particular types of crime (Brantingham & Brantingham, 1999:17, 18). Thus, the non-random distribution of crime at places can be understood by a cluster of etiologies under different physical, social, legal, cultural, economic and temporal environments because individuals live in the environments and their behaviors are tied to environmental backcloth (Brantingham & Brantingham, 1999). For this reason, some places are more favorable for criminal activities compared to others, which can result in variations in crime patterns (and potentially crime concentrations) across places.

Crime Concentrations at the Micro-Geographic Level

Environmental criminology, crime pattern theory, and routine activities, are all relevant to crime concentrations at places for two reasons. The first is that these theories made the crime event, not the criminal, the focal point of study (Weisburd, 2002). Second, these theories emphasized that specific situations, environments, routines, templates, and opportunities at places might be key factors in explaining why crime events occur at specific places and not others, which was a departure from more macro-sociological explanations like social disorganization and collective efficacy theories.

These theories led Sherman, Gartin, and Buerger (1989) to suggest that perhaps it was these theories that could explain the very specific crime concentration patterns they saw if their empirical analysis of police crime data, which didn't seem to follow patterns suggested by social disorganization theorists. Sherman et al. examined 323,979 police calls-for-service across 115,000 unique addresses and intersections in Minneapolis, Minnesota, from December 1985 to December 1986 to determine how crime concentrated. They found that crime was highly concentrated at individual addresses. When examining the highest crime addresses from most to least crime, they found that the top 3% of addresses in Minneapolis produced 50% of all calls to the police. Further, *all* robbery calls came from only 2.2% of places, *all* auto thefts came from 2.7% of places, and *all* rape calls came from 1.2% of all addresses. Sherman et al. hypothesized that if crime actually concentrates at much more specific places—even within neighborhoods or communities that seem depressed—then perhaps social disorganization scholars overgeneralized their explanations of the nature of crime across geography.

Perhaps even within neighborhoods defined by social disorganization, there was heterogeneity of crime concentrations at the street or address level (see also Sherman & Weisburd, 1995).

Using Brantingham and Brantingham's theory, Sherman et al. (1989) put forth a place-based routine activities theory, arguing that crime is not random, but instead results from opportunities and routines that are either generated at, or drawn to, specific places (in their work, addresses). In the parlance of routine activities theory, they hypothesized that this disproportional crime concentration across small places may result from the convergence in time and place of likely offenders, suitable targets, and absence of capable guardians against crime at those specific places. They argued that routine activities theory further explains variations in crime patterns across places at micro-place levels, while characteristics of people and space were only able to explain community-level variation.

Since Sherman et al., researchers have analyzed large amounts of crime data, which continue to show that crime concentrates at the micro level (see Pierce et al., 1988; Sherman et al., 1989; Sherman & Weisburd, 1995; Spelman, 1995). Early research focused on characteristics of very specific places. For instance, Repetto (1974) and Waller and Okihiro (1978) found that apartments in building with doormen were less likely to be burglarized than other apartments. Duffala (1976) found that convenience stores near vacant lands or away from the other places of commerce were more likely to be robbed than those in dense commercial areas. Clifton and Callahan (1987) and Davis (1987) discovered that different commercial stores have different rates of robbery.

Indeed, crime rates at places vary according to the number of clerks and their visibility, types of crimes, time, location of stores, and other physical characteristics of place (e.g. tunnels, bridges, low lighting areas, etc.).

Others have supported Sherman et al.'s initial finding with empirical analyses of crime concentrations across jurisdictions or other large places. In their famous hot spots experiment, Sherman and Weisburd (1995) found that around 11% of street addresses generated all the police calls-for-service in Minneapolis between December 1987 and November 1988, which became the foundation for their directed patrol or "hot spots" approach to reducing and preventing crime. Eck, Gersh, and Taylor (2000) found that the most active 10% of the crime places (street addresses) in the Bronx and Baltimore generated approximately one third of combinations of crimes including assaults, auto thefts, burglaries, grand larcenies, and robberies. Weisburd and Mazerolle (2000) similarly found that 56 drug hot spots (clustered street segments or street blocks) across different neighborhoods in Jersey City produced almost 20% of all disorder crimes and 14% of crimes against persons. This means that some active crime places have multiple crimes of different types (Eck et al., 2000). Braga et al. (2010) and Braga et al, (2011) examined violent crime in Boston and found gun violence and robbery rates were very high at a small number of street segments and intersections between 1980 and 2008.

The finding of crime concentration is not limited to the U.S.; Curman et al. (2015) found that less than 10% of street segments housed 60% of crime in Vancouver, Canada. Weisburd and Amram (2014) found that 50% of crime incidents in Tel Aviv-Jaffa were located in 5.6% of street segments. Jaitman and Ajzenman (2016) also found high crime concentration in five Latin America countries (Belo Horizonte in Brazil, Bogota in Colombia, Montevideo in Uruguay, Sucre in Venezuela, and Zapopan in Mexico) that 3 to 7.5% of street segments produce 50% of crime, and 0.5 to 2.9% of street segments generate 25% of crime. Further, studies have also shown that crime concentration might be very stable over time. Weisburd et al. (2004) found that over a 14-year period, 50% of the crime consistently occurred in approximately 4.5% of the street segments (see also Groff et al., 2010). Similarly, a very small percentage of street segments account for 50% of the various crime classifications in Vancouver, Canada over 16-year period (Andresen et al., 2016; Curman et al., 2015).

It should be noted that there is some disagreement about what constitutes a "micro" geographic unit, which may impact these micro-level calculations of the concentration of crime. Eck and Weisburd (1995) defined the micro place as "a very small area, usually a street corner, address, building, or street segment" (p. 33). Eck, Gersh, and Taylor (2000) emphasized street address or facilities, as a unit of analysis to understand crime patterns; Eck (2002) defined a place as "a small area reserved for a narrow range of functions, often controlled by a single owner, and separated from the surrounding area" (p. 241). For example, specific locations with high crime, such as stores, food restaurants, bars, pubs, supermarkets, bus and subway stops, intersections, and street corners have been used as units of analysis. Other scholars (e.g. see Weisburd, Groff, & Yang, 2012) have argued for the importance of street segments as a geographic unit of analysis; a street segment is defined as a street separated between two intersections, and the two block faces on either side of the street between two intersections. They argue that the street segment is an important unit of analysis to identify crime concentration because “using street segments allows a unit of analysis large enough to avoid unnecessary crime coding error, but small enough to avoid aggregation that might hide specific trends” (Weisburd et al., 2012:25; see also Weisburd et al., 2004; Weisburd et al., 2016). Nonetheless, whatever the definition used, it appears that the finding of high levels of crime concentration at very small units of geography has been common.

Weisburd’s Law of Crime Concentrations

The totality of these studies led Weisburd (2015) to suggest the existence of a “law of crime concentration at place.” He asserted 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, 2015:138). He based the law on the many studies that seem to find high crime concentration at smaller places (specifically, Andresen & Malleson, 2011; Andresen et al., 2016; Braga, Papachristos, & Hureau, 2014; Brantingham & Brantingham, 1999; Crow & Bull, 1975; Curman, Andresen, & Brantingham, 2015; Pierce, Spaar, & Briggs, 1988; Roncek, 2000; Sherman, Gartin, & Buerger, 1989; Weisburd & Amram, 2014; Weisburd et al., 2004; Weisburd & Green, 1994; Weisburd, Lawton, & Ready, 2012; Weisburd et al., 1992; Weisburd, Maher, & Sherman, 1992; Weisburd, Morris, & Groff, 2009). Specifically, he argues that these studies show that 50% of crime seems to concentrate in approximately 4% of street segments (when counting street segments in descending order of crime frequency as did Sherman et al., 1989) and 25% of crime occur in less than 1.5% of street segments.

Weisburd (2015) also included the calculation of crime concentration in eight additional cities to make his point, using both larger and smaller jurisdictions (as defined by population). The five large cites included Cincinnati (Ohio), New York City (New York), Sacramento (California), Seattle (Washington), and Tel Aviv-Yafo (Israel). The small cites he included in his analysis were Brooklyn Park (Minnesota), Redlands (California), and Ventura (California). Weisburd found that for both large and smaller cities have similar crime concentrations, which occur within a narrow bandwidth of percentages for a defined cumulative proportion of crime (although smaller cities seem to be more highly concentrated, as also found by Hibdon, 2013, and Gill et al., 2017).

Two recent studies have tested the salience of Weisburd's law of crime concentration with different cities of different sizes (Gill et al., 2017; Hipp & Kim, 2016). Table 1 shows the similarities and differences between Weisburd and Hipp and Kim's studies (Gill et al.'s study of Brooklyn Park, Minnesota, is included in Weisburd's article).

Table 1. Findings from the Prior Law of Crime Concentration Studies

Jurisdiction Characteristics	Studies of Law of Crime Concentration: Weisburd (2015)	Hipp and Kim (2016)
Population (290,000 above)	5 cities	5 cities
Number of street segments	13,550 to 87,279	5,450 to 73,991
Average length of street segments	56 to 136 meters	.
Population (100,000 to 290,000)	1 city	11 cities
Number of street segments	4,568	2,195 to 6,758
Average length of street segments	208 meters	.
Population (40,000 to 100,000)	2 cities	26 cities
Number of street segments	2,937 to 4,674	.
Average length of street segments	207 to 208 meters	.
Unit of analysis	Street segments	Street segments
Type of crime	Total crime, personal, property, disorder, drugs, prostitution, and traffic-related crimes (Incident)	Total crime, aggravate assault, robbery, burglary, motor vehicle theft, and larceny (Calls for service)
Concentration levels	4% of segments for 50% concentration, 1.5% segments for 25% concentration	5% of segments for 15 to 90% (*temporally adjusted*), 35 to 100% concentration (*historically adjusted*)

Note: Concentration levels are based on the total crime with Weisburd's (2015) measure.

Hipp and Kim (2016) examined 42 cities in southern California and found what they describe as a considerable amount of variability in the concentration of crime across cities, questioning Weisburd's law. They argue that while there is strong crime concentration in all of the cities they examined, the level of crime concentration varies significantly across cities, especially when examining the top 5% of street segments with the most crime. To adjust for this, they use two adjusted measures of crime concentration to take into account the year-to-year random spatial variation of crime, which may have led to such findings. In particular, they determined the top 5% of segments based on the sum of total number of crime events in each street segment over 5 to 8 years (a measured they label as "*historically adjusted").* Using these measures, they found that the top 5% of street segments could hold between about 35 to 100% of a city's crime. They also computed a "temporally adjusted" percent of crime events that occurred in the top 5% of segments in the current year based on the number of crime events in the prior year. Using these measures, they also found that the top 5% of segments could hold between about 15 to 90% of a city's crime. With these findings, they challenged Weisburd's idea of a "narrow bandwidth" of percentage of street segments as an essential condition for the law of crime concentration.

Hipp and Kim's (2016) findings challenge not only how Weisburd's law of crime concentration is calculated, but also the notion of a "law" itself (given the variability of crime concentration that they found). Further, as emphasized by Hipp and Kim, more research is also needed to understand why variations exist, if they do. There might be other social and structural factors that influence the level of crime concentration across jurisdictions (and not just the way concentrations are calculated).

The Current Study

This study continues to explore the salience of Weisburd's law of crime concentration. However, rather than focus on measurement adjustment as did Hipp and Kim, this study focuses on both generalizability of the law and explanations of variations in crime concentrations, if found. To explore generalizability, this study examines crime concentrations across all 43 policing jurisdictions in England and Wales in the United Kingdom. While the previous crime concentration studies in the Weisburd, Gill and Hipp and Kim's studies have randomly or selectively collected a handful of jurisdictions to examine Weisburd's Law, this study is the first to measure crime concentration of all jurisdictions within an entire country.

As will be discussed in greater detail, the UK police data—while having limitations—is useful to use when comparing variations of crime concentrations across jurisdictions because the crime report data is standardized for all 43 the jurisdictions. Therefore, the evaluation of crime concentrations within an entire country enables researchers to examine a range of bandwidths across varied jurisdictions. In turn, this can shed light on the salience of a law that states that crime tends to concentrate "within a narrow bandwidth of percentages for a defined cumulative proportion of crime" (Weisburd, 2015:132).

This study begins with the same calculation of crime concentration that Weisburd uses for purposes of comparison with his work. However, this study also uses the generalized Gini coefficient metric because it is useful to measure the statistical dispersion of crime concentration across jurisdictions, especially since there are many more places in which crime is measured (street segments) than there are crimes (see Bernasco & Steenbeek, 2017). The generalized Gini coefficient summarizes the level of crime concentration using a single number between 0 and 1. A “0” value reflects complete equality of crime concentration across jurisdictions while a value of “1” reflects complete inequality of crime concentration values across jurisdictions.

In this study, a range of the generalized Gini coefficient of .10 (the difference between minimum and maximum of Gini coefficient fall within .10) is arbitrarily set as a “narrow bandwidth” because the range falls within one-tenth of the distribution. For example, if levels of crime concentration among jurisdictions fall within Gini coefficient values of .80 and .90, then this suggests that there is a narrow bandwidth of crime concentration given this pre-set threshold. If the minimum and maximum values of the generalized Gini coefficient fall between .70 and .90, this range of .20 is less as narrow of a bandwidth. Because of the exploratory nature of this study, only further empirical work can determine what might be considered a “narrow” bandwidth.

To examine explanations of variations across jurisdictions, this study then examines whether selected characteristics of places (in which data was available) might be related to variations in crime concentration at places. In particular, previous research by Weisburd and also Gill shows that smaller cities tend to have higher crime concentration than larger cities. Thus, characteristics of places such as size, population density, or other physical aspects of places may be important factors in explaining the variety of crime concentrations found across jurisdictions of varying sizes. Closely related to these population and size characteristics are the layout of the behavioral settings and physical environments of places (Barker, 1978; Wicker, 1987). Although data was much more limited in terms of the physical environments of the 43 UK jurisdictions, this study also examines the length of street segments and population density as proxy measures of urbanization, as potential explanations of these variations. For example, longer street segments, which are often found in rural areas, may have less or more spatially dispersed opportunities for criminal activities compared to shorter street segments found in more highly urbanized locales.

Crime concentrations may also vary across jurisdictions with different socioeconomic and demographic characteristics. This study also examines whether other available measures of social disorganization (specifically used in this study are jobs density and proportion of non-white residents) can explain variations in crime concentrations across jurisdictions. Social disorganization theory posits that the availability of jobs and also ethnic heterogeneity may influence residential stability and social control, and thus levels of crime (in particular violence and property crime).

In addition to these physical and social characteristics of UK jurisdictions, calculations of crime concentrations may differ depending on what types of crime are being examined, a finding initially suggested by Sherman et al. (1989), and also found by Hipp and Kim. Therefore, this study also measures the levels of crime concentration for different crime types (all crime, violence, property crime, disorder/drug crimes).

CHAPTER THREE: RESEARCH METHODS

Location of the Study

This study examines all 43 police force jurisdictions in England and Wales. The United Kingdom does not have one national police service. Scotland and Northern Ireland have their own police services, which are governed separately, while the 43 police forces in England and Wales are under the purview of the Home Office of the United Kingdom. These 43 jurisdictions were delineated by the Police Act of 1996[1] and are shown in Figure 1.[2] Each police force in England and Wales covers its own territorial boundary and has an independent police authority that governs police policy. Each of the 43 forces are overseen by a Police and Crime Commissioner (PCC), with the exception of Greater Manchester and London, where PCC responsibilities lie with the Mayor (Association of Police and Crime Commissioners, 2017). Her Majesty's Chief Inspector of Constabulary and Fire and Rescue Services (HMICFRS, prior to 2017, HMIC) oversees the inspection of these 43 forces.

[1] See legislation.gov.uk.

[2] The City of London Police is not easily seen in Figure 1 because it is the smallest jurisdiction (2.9 km²), and is located in the middle of Metropolitan Police Service (1,569 km²), although separate from it.

Figure 1. 43 Police Forces across England and Wales

Source: Police force boundary (data.police.uk, 2017a).

While other studies, including those reviewed and examined by Weisburd (2015) and Hipp and Kim (2016), have examined crime concentration for specific cities within a larger political jurisdiction, the purpose of selecting all jurisdictions within the U.K. is to determine whether the law of crime concentration holds true across all places within a large, identifiable political jurisdiction that uses standardized measures of crime reporting. The 43 jurisdictions in England and Wales are also ideal to study because all crime data with specific geographic locators for each crime event is publicly available for all 43 police jurisdictions in a single data source known as the Open Government Website for Public Information (see http://data.police.uk and https://www.nationalarchives.gov.uk/doc/open-government-licence/version/3/). Such standardized and specific data would not be available across jurisdictions in the United States, or even within one U.S. state, given the decentralized nature of police services in the U.S.[3] Moreover, there are different laws, norms, and definitions of crime categories across states and even counties and towns in the U.S., which makes hard to compare one place to another.

These forty-three areas of England and Wales are also diverse with regard to social, economic, and demographic characteristics according to the most recent U.K. Census. Because police areas in the U.K. are aligned with county lines as delineated by the U.K, Census, census data is available to study the relationship between socioeconomic characteristics of jurisdictions and levels of crime concentration. Table 2

[3] For example, neither the Uniform Crime Reporting (UCR) system of the Federal Bureau of Investigation nor the National Incident Based Reporting System (NIBRS) provides individual information on all crimes that are reported into the system and where they occurred.

shows the heterogeneity across these jurisdictions with regard to the size of the jurisdiction, population, population density, and number of police officers, all which could impact crime patterns and the concentration of crime according to environmental criminology. Some of the 43 territorial police jurisdictions also include more than one city, as there are 51 cities in England and five in Wales (UK Cities, 2017)[4]. The UK jurisdictions are also different from the cities studied in Weisburd (2015), Gill et al., (2017), or Hipp and Kim (2016). For example, the five large cities in Weisburd (2015) (Cincinnati, Seattle, Tel Aviv-Yafo, New York, Sacramento) have much higher population density (on average, 4,743 people per square kilometer)[5] than the U.K. jurisdictions (on average, 383 per square kilometer) (see Table 2). This discrepancy compared to Weisburd (2015) means that our results must be interpreted cautiously. At the same time, a universal law would suggest that there should also be strong generalizations that exist.

[4] Cities in the U.K. do not necessarily designated a higher population density than non-cities.
[5] The population density of the five large cities from Weisburd (2015) article was calculated based on the population from his article. The area of four US cities are obtained from US Census 2010 https://www.census.gov/geo/maps-data/data/gazetteer2010.html. The area of Tel Aviv-Yafo is obtained from Wikipedia https://en.wikipedia.org/wiki/Tel_Aviv

Table 2. Area, Population, Population Density, and Number of Police Officers for the 43 Police Force Jurisdictions in England and Wales

Police Force	Area (km²)	Population	Population density (km²)	Number of Police Officers	Police Officer per 1,000 Population
Avon and Somerset	4,777	1,664,200	348	2,684	1.6
Bedfordshire	1,235	655,000	530	1,067	1.6
Cambridgeshire	3,390	841,200	248	1,339	1.6
Cheshire	2,343	1,043,500	445	2,010	1.9
City of London	2.9	8,800	3,034	688	78.2
Cleveland	597	562,100	942	1,299	2.3
Cumbria	6,767	498,000	74	1,102	2.2
Derbyshire	2,625	1,036,600	395	1,719	1.7
Devon & Cornwall	10,269	1,720,900	168	2,913	1.7
Dorset	2,653	765,700	289	1,220	1.6
Durham	2,424	625,100	258	1,125	1.8
Dyfed-Powys	10,955	515,900	47	1,171	2.3
Essex	3,670	1,787,000	487	2,806	1.6
Gloucestershire	2,653	617,200	233	1,067	1.7
Greater Manchester	1,276	2,756,200	2,160	6,234	2.3
Gwent	1,552	581,800	375	1,162	2.0
Hampshire	4,149	1,953,700	471	2,898	1.5
Hertfordshire	1,643	1,166,300	710	1,909	1.6
Humberside	3,517	925,100	263	1,542	1.7
Kent	3,736	1,801,200	482	3,193	1.8
Lancashire	3,075	1,478,100	481	2,787	1.9
Leicestershire	2,538	1,056,000	416	1,794	1.7
Lincolnshire	5,921	736,700	124	1,062	1.4
Merseyside	645	1,398,000	2,167	3,561	2.5
Metropolitan	1,569	8,665,000	5,523	31,782	3.7
Norfolk	5,371	885,000	165	1,505	1.7
North Wales	6,150	694,500	113	1,442	2.1
North Yorkshire	8,310	809,100	97	1,346	1.7
Northamptonshire	2,364	723,000	306	1,209	1.7
Northumbria	5,553	1,437,500	259	3,263	2.3
Nottinghamshire	2,159	1,124,700	521	1,893	1.7
South Wales	2,079	1,307,000	629	2,850	2.2
South Yorkshire	1,552	1,374,700	886	2,460	1.8
Staffordshire	2,714	1,114,200	411	1,611	1.4
Suffolk	3,800	741,900	195	1,119	1.5

Surrey	1,662	1,168,800	703	1,896	1.6
Sussex	3,782	1,665,600	440	2,569	1.5
Thames Valley	5,740	2,358,600	411	4,200	1.8
Warwickshire	1,975	554,000	281	853	1.5
West Mercia	7,408	1,249,200	169	2,093	1.7
West Midlands	902	2,833,600	3,141	6,880	2.4
West Yorkshire	2,029	2,281,700	1,125	4,556	2.0
Wiltshire	3,485	703,300	202	976	1.4
England & Wales (Total)	151,017	57,885,700	.	122,855	.
England & Wales (Average)	3,512	1,346,179	383	2,857	2.1

Source: Area (Nomisweb.co.uk, 2017a); Population in 2015 and Number of Police in 2015 (UK Office for National Statistics, 2016a).

Using all jurisdictions across a political landscape allows for the analysis of other exogenous variables (i.e. gross disposable household income, unemployment, jobs density [the number of jobs divided by the number of residents of employable age], lone parent with dependent child(s), and non-white), which have been informed by social disorganization theory, that might explain the variability of crime concentration across jurisdictions, also not previously examined. Additionally, characteristics of street segments, such as their density, length, or number may significantly impact crime concentrations because the specific environmental contexts can influence the opportunity structures for criminal activities.

Some of this additional heterogeneity can be seen in Table 3. The Gross Disposable Household Income (GDHI) is the amount of money that all of the individuals in the household sector have available for spending or saving after income distribution measure. The GDHI per head index shows each jurisdiction relative to the UK as a whole

(UK = 100). The values below 100 indicate a jurisdiction has less disposable income than the UK average, whereas values over 100 indicate a jurisdiction has more disposable income than the UK average (Office for National Statistics, 2016). The lowest GDHI of police force is Lancashire, and the highest is the City of London. The range of unemployment varies from 3.8% (the City of London and Surrey) to 10.7% (Cleveland). The jobs density may account for the lack of economic opportunities across jurisdictions except for the City of London, Devon and Cornwall, and Thames Valley; the percent of jobs density is calculated as the number of jobs in an area divided by the total population aged 16-64. The City of London has the lowest single-parent families (2.1%), whereas Merseyside has the highest (9.5%). These jurisdictions differ in terms of racial make-up; some areas have a high non-white population, such as Metropolitan (51.8%) and the City of London (37.7%), while others consist of a small non-white population, such as Cumbria (3.7%), Durham (4.8%), and North Wales (4.9%). According to the descriptive analysis of physical and demographic characteristics of jurisdictions, the City of London has significant differences in population density, number of police officers per population, income, unemployment, jobs density, and lone parent with child(s) compare to other jurisdictions. Hence, it is important to note that the City of London is an outlier.

Table 3. Gross Disposable Household Income (GDHI) per Head Index, Unemployed, Jobs Density, Lone Parent with Dependent Child(s), and None-White for the 43 Police Force Jurisdictions in England and Wales

Police Force	GDHI per head index (UK = 100)	Un-employment (%)	Jobs density (%)	Lone parent with dependent child(s) (%)	Non-white (%)
Avon and Somerset	101	4.4	0.86	6.4	10.3
Bedfordshire	93	6.4	0.71	7.4	29.8
Cambridgeshire	97	5.6	0.92	6.4	20.6
Cheshire	100	5.9	0.91	7.4	5.9
City of London	2,386	3.8	84.29	2.1	37.7
Cleveland	83	10.7	0.68	9.3	6.5
Cumbria	99	4.8	0.90	5.7	3.7
Derbyshire	84	6.6	0.78	7.2	13.7
Devon & Cornwall	101	4.7	1.05	5.5	5.4
Dorset	103	4.7	0.85	5.4	9.6
Durham	83	7.2	0.76	8.2	4.8
Dyfed-Powys	89	5.1	0.79	6.4	5.0
Essex	99	6.6	0.71	6.9	13.7
Gloucestershire	108	4.5	0.89	5.2	8.6
Greater Manchester	86	7.2	0.75	8.5	17.8
Gwent	84	7.8	0.66	8.1	5.2
Hampshire	92	5.8	0.82	7.0	12.2
Hertfordshire	123	4.7	0.90	6.4	20.0
Humberside	80	8.4	0.75	7.4	6.5
Kent	99	6.2	0.68	7.3	12.8
Lancashire	79	7.7	0.78	8.3	16.0
Leicestershire	86	5.8	0.82	6.3	22.6
Lincolnshire	90	5.6	0.75	5.8	7.3
Merseyside	85	8.7	0.67	9.5	6.6
Metropolitan	135	7.2	0.91	8.4	51.8
Norfolk	91	5.6	0.80	5.6	7.4
North Wales	89	6.1	0.78	6.6	4.9
North Yorkshire	99	4.3	0.91	5.6	7.9
Northamptonshire	97	5.4	0.83	7.3	15.2
Northumbria	83	7.9	0.75	7.9	6.6
Nottinghamshire	80	8.0	0.88	8.0	18.6
South Wales	81	7.1	0.69	8.2	6.9
South Yorkshire	82	7.8	0.69	7.5	9.8
Staffordshire	83	6.6	0.76	7.2	10.0

Suffolk	98	5.1	0.83	5.9	9.4
Surrey	142	3.8	0.91	4.7	17.7
Sussex	108	5.0	0.81	6.2	13.0
Thames Valley	118	4.8	0.97	6.3	24.2
Warwickshire	106	4.8	0.94	6.1	12.5
West Mercia	95	5.3	0.81	6.2	7.7
West Midlands	80	9.4	0.75	8.5	27.2
West Yorkshire	83	7.3	0.79	7.5	19.8
Wiltshire	102	4.8	0.88	6.4	10.9

Source: GDHI per Head Index in 2015 (UK Office for National Statistics, 2016b); Unemployment in 2011 (Nomisweb.co.uk, 2017b); Jobs Density in 2015 (Nomisweb.co.uk, 2017c); Lone Parent with Dependent Child(s) in 2011 (Nomisweb.co.uk, 2017d); Non-white in 2011 (Nomisweb.co.uk, 2017e).

Data

As aforementioned, England and Wales are an excellent location to test Weisburd's law of crime concentration across a large political jurisdiction because standardized crime data is publicly available for all 43 police force jurisdictions, which includes the latitude-longitude coordinate of each crime event. Following Weisburd's approach, this study uses a single year of data from data.police.uk (2016), which was downloaded in March 2017. The fields that are provided in this data include:

- "Reported by": denotes the police force that provided the data about the crime.
- "Falls within": denotes the police jurisdiction where the crime occurred (which could be different than the force that reported the crime)
- "Longitude" and "Latitude": denotes the approximate x-y coordinates of the crime (the specific address of the crime is not given).
- "Crime type" includes the following categories:
    - All crime—a total for all crime categories.
    - Anti-social behavior—personal, environmental and nuisance anti-social behavior.
    - Bicycle theft—the taking without consent or theft of a pedal cycle.
    - Burglary—offences where a person enters a house or other building with the intention of stealing.
    - Criminal damage and arson—damage to buildings and vehicles and deliberate damage by fire.

    - Drugs—offences related to possession, supply and production.
    - Other crime—forgery, perjury, and other miscellaneous crime.
    - Other theft—theft by an employee, blackmail and making off without payment.
    - Possession of weapons—such as a firearm or knife.
    - Public disorder and weapons—offences which cause fear, alarm, distress or a possession of a weapon such as firearm.
    - Public order—offences which cause fear, alarm or distress.
    - Robbery—offences where a person uses force or threat of force to steal.
    - Shoplifting—theft from shops or stalls.
    - Theft from the person—crime that involve theft directly from the victim (including handbag, wallets, cash, mobile phones) but without the use or threat of physical force.
    - Vehicle crime—theft from or of a vehicle or interference with a vehicle.
    - Violence and sexual offences—offences against the person such as common assault, grievous bodily harm, and sexual offences.
- "Last outcome category": this is a reference to whichever of the outcomes associated with the crime occurred most recently. For example, 'Offender fined'.
- "Context": a field provided for forces to provide additional human-readable data about individual crimes (data.police.uk, 2017b).

The fields used for this study are "Falls within," the XY longitude and latitude coordinates, and the "crime type" indicator. The type of crime is important for this study because the level of crime concentration may vary depending on the types of crime used in calculating crime concentrations. To simplify, crime types were aggregated into four categories for this study: "all crime," "property crime," "violent crime," and "disorder/drugs crime." Property crime includes bicycle theft, burglary, criminal damage and arson, other theft, shoplifting, theft from the person, and vehicle crime. Violent crime contains robbery, violence and sexual offences. Disorder/drugs includes antisocial behavior and drugs.

While this is the only publicly available data for England and Wales, it should be noted that there are challenges with this data that may impact this analysis For example, the data.police.uk records always represent the approximate location of a crime for privacy protection (see https://data.policeuk/about/#anonymisation), which could underestimate real incident locations (see Tompson, Johnson, Ashby, Perkins, & Edward, 2015) and possibly impact on the level of crime concentration. The implications of this limitation will be discussed in Chapter 4 and 5.

Analytic Strategy

Using the same street segments as defined by Weisburd (2015) for the spatial unit of this analysis, the geocoding program ArcGIS was used to assign each crime to the closest street segment, which then is summed to give the total number of crime events which occur at any given street segment. A small amount of the crime—1.2 percent—could not be assigned to a specific jurisdiction because it lacked reliable address information and was removed from the analysis. There is no crime incident at intersection because data.police.uk uses a master list of anonymous map points to appear locations over the centre point of street or above a public space or commercial premise.[6] This study uses Open Roads data from Ordnance Survey to create street segments, which was downloaded in 2014 (see https://www.ordnancesurvey.co.uk/business-and-government/products/os-open-roads.html). Both roads and crime locations are mapped with the same coordinate system (World Geodetic System 1983).

Table 4 shows, the total number of street segments, the sum length of the street segments, the mean length of the street segments, and standard deviation (SD) length of

[6] The data.police.uk recodes always represent the approximate location of a crime – not the exact place for privacy protection. See https://data.police.uk/about/#anonymisation

the street segments in each of the forty-three forces. As Table 4 indicates, there are approximately 2.8 million street segments in England and Wales. The average length of these street segments is 161 meters, and the average standard deviation (SD) length of street segments length is 236 meters. Importantly, most police force areas are large and may include urban, suburb, and rural areas. The consequences of this to the analysis forthcoming will be discussed in Chapters 4 and 5.

Table 4. Descriptions of Street Segments in 43 Jurisdictions

Police Force	Number of Street Segments	Sum Length of Street Segments (kilometers)	Mean Length of Street Segments (meters)	SD Length of Street Segments (meters)
Avon and Somerset	87,501	1,485	166	258
Bedfordshire	24,260	3,708	153	237
Cambridgeshire	41,487	7,629	184	184
Cheshire	58,706	8,465	144	206
City of London	938	65	69	51
Cleveland	29,374	3,159	108	150
Cumbria	48,405	11,172	231	369
Derbyshire	49,282	7,906	160	244
Devon & Cornwall	135,573	28,579	211	285
Dorset	40,287	6,970	173	266
Durham	41,099	5,835	142	247
Dyfed-Powys	70,538	21,855	310	401
Essex	73,640	11,406	155	225
Gloucestershire	38,745	7,229	187	282
Greater Manchester	128,494	10,934	85	101
Gwent	35,744	5,566	156	246
Hampshire	94,003	14,003	149	223
Hertfordshire	47,590	6,466	136	198
Humberside	48,452	8,403	173	298
Kent	79,513	12,577	158	223
Lancashire	92,660	10,802	117	183
Leicestershire	44,074	7,193	163	257
Lincolnshire	47,606	11,660	245	388
Merseyside	59,074	5,702	97	112
Metropolitan	176,558	17,225	97	97
Norfolk	58,900	12,585	214	320
North Yorkshire	61,889	14,539	235	375
Northamptonshire	35,903	5,851	163	269
Northumbria	84,269	12,760	151	288
North Wales	65,715	14,199	216	320
Nottinghamshire	47,283	7,049	149	229

South Wales	66,078	8,362	127	198
South Yorkshire	58,326	6,981	120	175
Staffordshire	58,782	8,944	152	220
Suffolk	45,279	9,025	199	290
Surrey	54,832	7,424	135	169
Sussex	75,970	11,597	153	209
Thames Valley	110,785	17,084	154	234
Warwickshire	31,116	5,504	177	265
West Mercia	87,890	18,566	211	295
West Midlands	86,820	8,839	102	100
West Yorkshire	110,071	11,533	105	145
Wiltshire	40,709	7,664	188	311
England & Wales (Total)	2,774,220	424,521	.	.
England & Wales (Average)	64,517	9,873	161	236

Source: Author's estimation with Open Road shapefile from Ordnance Survey (Ordnance Survey, 2014).

Once crimes were geocoded to street segments, four types of crime concentrations were calculated, using the same approach used by Weisburd (2015), again, for a fair comparison. These included the percentage of street segments (ranked from most to least crime) that house 25%, 50%, 75% and 100% of crime. The crime concentrations were calculated by generating a frequency count of crime for each street segment, then sorting segments in descending order by crime counts. The proportion of total crime (or type of crime) for each segment was calculated, along with a cumulative proportion of crime from segments with the most to the least crime. Additionally, crime concentrations were calculated for four types of crime: all crime, property, violence, and disorder/drugs.

A hypothetical example of these calculations is shown in Table 5. Imagine there are 100 street segments in an imaginary city that had 1,000 crimes in 2016. Table 5 shows each of these street segments listed in descending order based on the total crimes that occur on them. The 100 block of Main Street has 12.5% of all crimes (i.e., 125/1,000), 200 block of Smith street has 12% of all crimes, and so on. Notice how at 4400 block of Park Avenue, the cumulative amount of crime almost reaches 50%—thus, in this example, approximately 50% of all crime occurs in six (or 6%) of the 100 street segments in this city. Similarly, 25% of all crime occurs in approximately 2 (or 2%) of street segments. This type of calculation is created for each of the 43 jurisdictions, for all for crime types, and at each level of crime proportion (25%, 50%, 75%, 100% of crime).

Table 5. Hypothetical Cumulative Amount of Crime by Street Segments

Street	Number of Crimes	Proportion of total crimes	Cumulative Proportion of crimes
100 block of Main Street	125	0.125	0.125
200 block of Smith Street	120	0.12	0.245
6600 block of Park Street	98	0.098	0.343
900 block of Luther Street	77	0.077	0.42
3600 block of 1st Avenue	45	0.045	0.465
4400 block of Park Avenue	24	0.024	0.489
…	…	…	…
…	…	…	…

(Based on example of total of 1000 crimes, and 100 street segments. Some street segments may have 0 crimes.)

As a fair comparison, this study uses Weisburd's calculation to determine the salience of the law if that specific calculation was used. Additionally, listing segments in descending order of crime frequency calculates the crime concentration levels for segments with the greatest amount of crime. However, this study also uses the generalized Gini coefficient to discuss variations in crime concentrations. The generalized Gini coefficient has been recommended by researchers for this purpose because the coefficient can measure the inequality of statistical dispersion of crime concentration across places (see discussions by Bernasco & Steenbeek, 2017). These researchers argue that when the total number of spatial units of analysis (street segments) outnumbers the total number of crime in a given analysis, there is no perfect equality because crimes cannot be equally divided by places. Bernasco and Steenbeek (2017) suggest that the generalized Gini coefficient is more useful in the case of fewer crimes than places, which is the case in this study especially when considering specific categories of crime (violence, property, drugs/disorder) (see Appendix, Table A1). For this analysis, the "sgini" Stata command is used to calculate the generalized Gini coefficient for jurisdictions by crime types (see Kerm, 2009), and the coefficients will be then compared to the findings of crime concentration using the arbitrary cutoffs such as 25, 50, 75, and 100% of crime.

The crime concentration calculations will then be regressed against a variety of co-variates that characterize each jurisdiction. In particular, variables related to social disorganization, such as unemployment rate, income, jobs density, percentage of lone parent with dependent child(s), and percentage of non-white will be used to understand whether the macro-level social characteristics influence variations in crime concentrations, if any. Physical characteristics of jurisdictions (population density, number of street segments, and mean length of street segments) will also be examined to explain the variability of crime concentration. Since the City of London is significantly different in social and physical characteristics from other jurisdictions (see Tables 3 and

4), the City of London is excluded from the regression analysis.

CHAPTER FOUR: ANALYSIS AND RESULTS

Overall Crime Concentration Calculations

Table 6 shows, for all crime, the average percentage of street segments in which each proportion of crime is concentrated, using Weisburd's calculation for all 43 jurisdictions in England and Wales. To reiterate, the crime amounts of "25%", "50%", etc. refer to the cumulative amount of crime at street segments if they are arranged in descending order as in Table 5. All types of crime are included in these calculations.

Table 6. Crime Concentrations at Street Segments for 43 Jurisdictions by Crime Amounts

Crime Amounts	Percentage of Street Segments			
	M (%)	SD (%)	Min (%)	Max (%)
25% of Crime	0.64	0.25	0.27	1.81
50% of Crime	2.47	0.81	1.01	5.44
75% of Crime	6.46	1.86	2.57	12.69
100% of Crime	20.76	5.11	7.95	35.61

Note: M=Mean. SD=Standard Deviation. Min (%)=The smallest percentage of crime concentrations among jurisdictions. Max (%)=The largest percentage of crime concentrations among jurisdictions.

Overall, Table 6 shows that crime concentrates at a very small percentage of street segments, no matter the amount of crime examined, with the exception of 100% of crime. This descriptive finding generally supports Weisburd's law of crime concentration. However, these findings also indicate that there may be considerable variability of crime concentrations across jurisdictions and across levels of crime, and that these variations are noteworthy. For example, across different crime levels used, there is also great variation. While 25% of the crime on average is concentrated at less than 1% of all segments, this almost quadruples when 50% of the crime is used and further almost triples when 75% of all crime is included. These average concentrations seem much higher compared to the jurisdictions in Weisburd's (2015) study. Recall, in Weisburd et al. (2015), 25% of crime occurred on average in about 1.5% of street segments, and 50% of crime occurred in approximately 4% of street segments.

Further, the average mean percentage of street segments in which 25% of all crime is concentrated across these jurisdictions is 0.64%, but with a standard deviation of 0.25; for 50% of the crime is concentrated in 2.47% (s.d. = 0.81); for 75% of the crime is concentrated in 6.46% (s.d. = 1.86); and 100% of all crime is concentrated in 20.76% (s.d. = 5.11). The minimum and maximum values of the mean also show the variability of this concentration across these 43 jurisdictions. So for example, while 25% of all crime on average was concentrated in 0.64% of street segments across the U.K., depending on the police force, this concentration could range between 0.27% and 1.81%. In other words, some jurisdictions have extraordinarily high concentrations of crime at this proportion of crime compared to the average. This variability can be seen at 50%, 75% and 100% of the crime.

The inclusion of one jurisdiction—the City of London—could be influencing these results. The City of London is an outlier both politically and geographically, and because of the significant differences in social and physical characteristics from other jurisdictions, as already shown in Tables 3 and 4. Thus, Table 7 shows the crime concentration means excluding the City of London.

Table 7. Crime Concentrations at Street Segments for 42 Jurisdictions (Excluding the City of London) by Crime Amounts

Crime Amounts	Percentage of Street Segments			
	M (%)	SD (%)	Min (%)	Max (%)
25% of Crime	0.61	0.18	0.27	1.08
50% of Crime	2.40	0.67	1.01	4.09
75% of Crime	6.31	1.60	2.57	10.26
100% of Crime	20.40	4.60	7.95	30.13

Note: M=Mean. SD=Standard Deviation. Min (%)=The smallest percentage of crime concentrations among jurisdictions. Max (%)=The largest percentage of crime concentrations among jurisdictions.

When the City of London is removed, the average percentages of street segments that house 25, 50, 75, and 100 percent of the crime are smaller (i.e., crime appears slightly even more concentrated, on average). For example, 50% of the crime occurs on average in 2.40% (s.d. = 0.67) of street segments (compared to Weisburd's 4%), with a minimum of 1% and a maximum of 4.1% respectively. Again, while these differences may seem trivial, because 100% crime is already concentrated at a small proportion of street segments, such differences could be interpreted as significant.

Crime Concentration by Crime Type

Crime concentrations may also vary across crime types. Table 8 shows the crime concentrations by crime type, for each proportion of crime, again excluding the City of London. While 25% of all crime appears to fall, on average, in 0.61% (s.d. = 0.18) of street segments, when examining only violence, property crime, or disorder and drug crimes, this percentage of street segments is smaller, and the difference between these concentrations and the concentrations of all crime appear statistically significant. For example, 25% of violent crime occurs in 0.53% (s.d. = 0.18); 25% of property crime is concentrated in 0.41% (s.d. = 0.11) of street segments; and 25% of disorder and drug crimes are concentrated in 0.51% (s.d. = 0.15) of street segments, on average across the 42 jurisdictions. This pattern (specific crime categories are more concentrated than all crime generally) is repeated for 50%, 75% and 100% of crime. Significant differences between crime concentrations also occur when crime types are compared with each other, except in the case of disorder and drug crimes, which appear to be similarly concentrated as violent crimes except when examining 100% of the crime.

Table 8. Crime Concentrations at Street Segments for 42 Jurisdictions by Crime Amounts and Types (Excluding the City of London)

Crime Amounts with Types	Percentage of Street Segments				Paired t-test		
	M (%)	SD (%)	Min (%)	Max (%)	All Crime	Violent	Property
25% of Crime							
All Crime	0.61	0.18	0.27	1.08			
Violent	0.53	0.18	0.19	1.12	7.15***		
Property	0.41	0.11	0.20	0.71	16.73***	7.40***	
Disorder/Drug	0.51	0.15	0.25	0.81	8.80***	0.83	-7.70***
50% of Crime							
All Crime	2.40	0.67	1.01	4.09			
Violent	1.92	0.61	0.74	3.86	14.93***		
Property	2.02	0.58	0.85	3.37	15.14***	-2.83**	
Disorder/Drug	1.87	0.50	0.86	2.85	12.57***	0.92	3.60**
75% of Crime							
All Crime	6.31	1.60	2.57	10.26			
Violent	4.67	1.37	1.84	8.92	21.48***		
Property	5.69	1.57	2.21	9.51	15.87***	-14.09***	
Disorder/Drug	4.82	1.18	2.11	6.91	15.26***	-1.31	8.29***
100% of Crime							
All Crime	20.40	4.60	7.95	30.13			
Violent	11.74	3.54	4.27	23.68	28.74***		
Property	16.37	4.65	5.35	28.16	30.70***	-17.71***	
Disorder/Drug	14.24	3.71	6.00	21.55	21.12***	-7.27***	6.40***

Note: M=Mean. SD=Standard Deviation. Min (%)=The smallest percentage of crime concentrations among jurisdictions. Max (%)=The largest percentage of crime concentrations among jurisdictions. Paired t-test= comparing two sample means of crime concentrations by crime type.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

As with overall crime concentrations, the minimum and maximum range of crime concentration for each crime type can also vary across jurisdictions as shown in Table 8. For example, 50% of property crime can occur between 0.85% and 3.37% of street segments, depending on the jurisdiction.

Street Segment Length and Crime Concentrations

As discussed in Chapter 2 and 3 and as also presented by Hipp and Kim (2016), crime concentrations calculations may be influenced by a number of factors. Here we explore the possibility that using the spatial unit of analysis of the street segment may artificially inflate or deflate crime concentrations depending on the length of the street segments used. Longer street segments, for example, may have more opportunities for crime to occur on them than shorter ones. If some jurisdictions tend to have longer street segments (this is sometimes the case in more rural areas), this could influence crime concentrations for all crime and for specific types of crime.

To examine this issue further, Figure 2a – 2d shows scatter plots for crime concentrations of property and violent crime at 25, 50, 75, and 100% of crime. The x-axis is the mean street segment length for each of the 43 jurisdictions (here we include the City of London). The y-axis shows the percentage of street segments that hold the noted level of crime for each graph (25%, 50%, etc.). Overall, Figures 2a – 2d show that when jurisdictions have, on average, shorter street segments, crime is *less* concentrated no matter the crime amount level examined. In other words, jurisdictions that have shorter street segments have greater proportions of street segments with crime compared to jurisdictions who have longer street segments. If less populated areas tend to have longer street segments (which they do), this adds an additional clue to the finding by Hibdon (2013), Gill et al. (2017), and Weisburd (2015) that less populated suburban and rural areas (which tend to have longer street segments) appear to have greater concentrations of crime.

However, an interesting finding is revealed in Figure 2. When looking at the highest-crime street segments that house 25% of crime (Figure 2a), one can see that no matter the mean segment length in the jurisdiction, property crime (marked as blue diamond and solid blue line for exponential line) is comparatively more highly concentrated than violence (marked as red square and dash red line for exponential line). However, this pattern does not hold when examining larger proportions of crime. Figure 2b shows that when examining how 50% of crime concentrates at segments, the high level of property crime concentration begins to drop, reaching similar crime concentrations of violent crime at 50% concentration for jurisdictions with varying street segment average lengths. This change is even more stark when looking at the concentration of 75 and 100% of each category of crime. Notice in Figures 2c and 2d, violence starts to appear much more concentrated across jurisdictions with varying street segment lengths than property crime, the more amount of crime that is used for the crime concentration calculation.

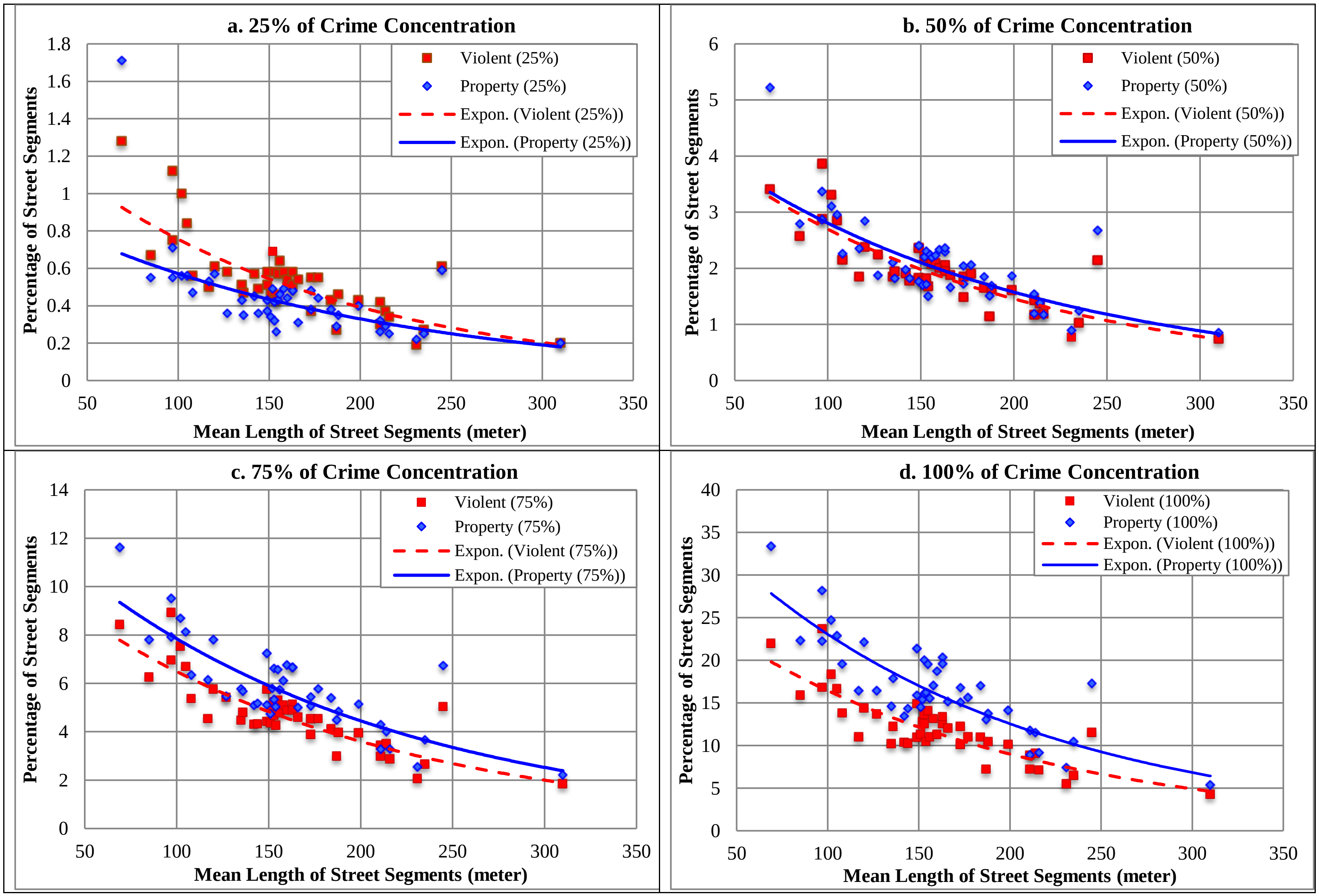

Figure 2. Crime Concentrations of Property and Violent Crime for 43 Jurisdictions By Length of Street Segment

The phenomenon seen in Figure 2, however, does not repeat itself when comparing violence with disorder and drug crimes. Figures 3a – 3d show the crime concentration calculations for 25, 50, 75, and 100% of crime across different average street segment lengths for violence and drug/disorder crimes. Here, when crime concentration is calculated for 25% of crime in the highest crime street segments, for places with small street segments, violence appears less concentrated that drug and disorder crimes. However, at larger street segments, the opposite appears to be the case (Figure 3a). This pattern is repeated for 50% and 75% of the crime, although, it appears that the greater proportion of crime used for the calculation, violence is only less concentrated for those places with smaller street segments (Figures 3b and 3c). However, when examining crime concentration levels when 100% of crime is used in the calculation, violence appears more concentrated than drug and disorder crime (Figure 3d). Thus, although the statistical difference of mean values for crime concentration between violent and disorder/drug crime is not significant (see Tables 6 and 7), Figure 3 illustrates a higher violent crime concentration at 100% concentrations and stronger violent crime concentration in jurisdictions with longer street segments.

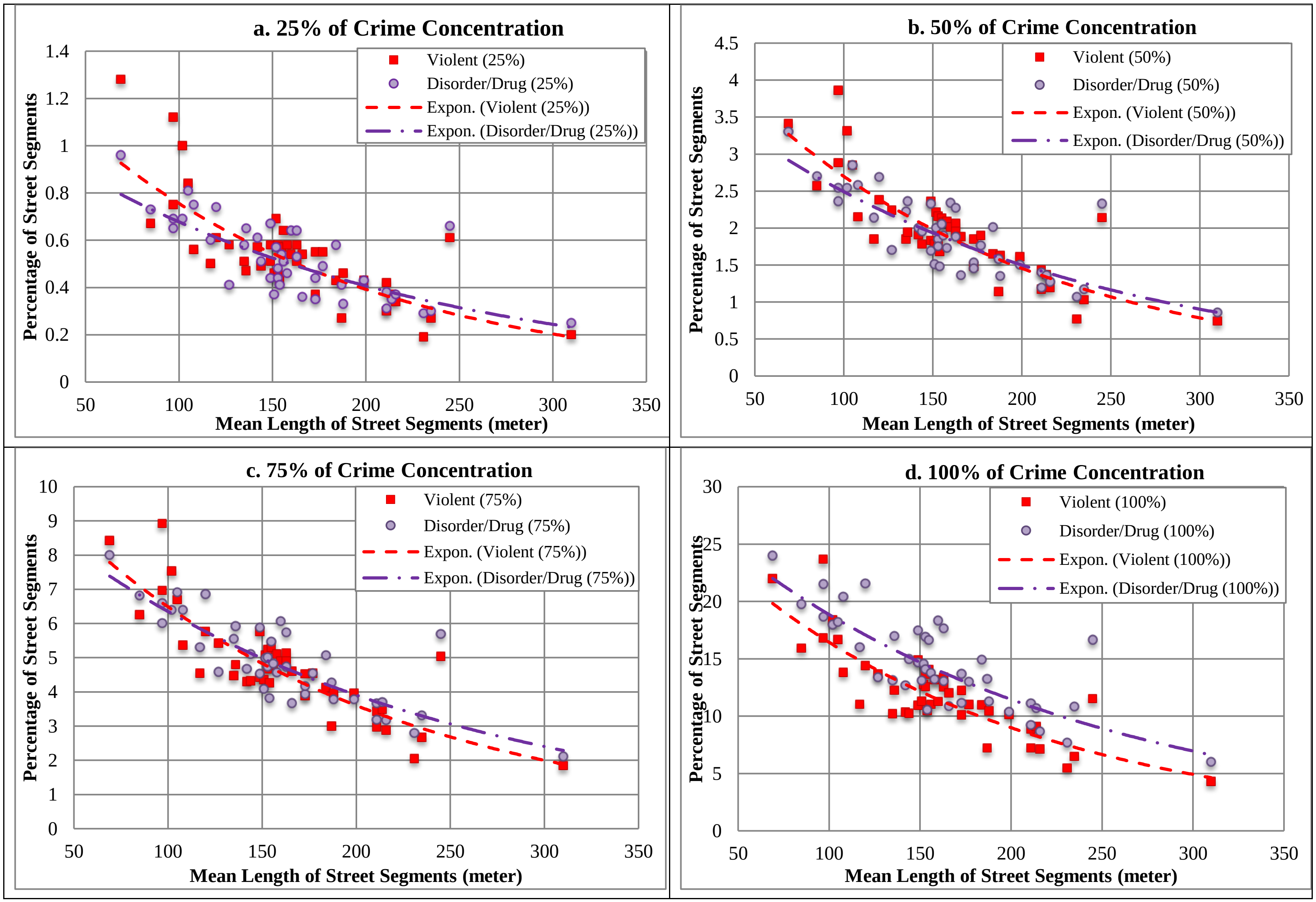

Figure 3. Crime Concentrations of Violent and Disorder/Drug Crime for 43 Jurisdictions By Length of Street Segment

Again, these nuances arise when comparing property and drug and disorder crimes (Figures 4a – 4d). Figure 4a shows property crime is more highly concentrated in smaller places than disorder/drug crime at 25% concentration, and this pattern reverses at higher percent concentrations (Figures 4b, 4c, and 4d). The level of property crime concentration tends to noticeably decrease at 100% crime concentration compared to disorder/drug crime (Figure 4d). The high property crime concentration at 25% concentration (Figure 4a) is also seen in Figure 2a, which seems to suggest that property crime is much more concentrated when looking at the highest crime segments, than when including all segments that have crime. The decreases of property crime concentrations at 50, 75, and 100% concentrations are apparent among jurisdictions with shorter mean length of street segments. The solid blue exponential lines indicate significant changes property crime concentrations compared to disorder/drug crime. Although only a hypothesis, it could be the case that high commercial districts which may be on shorter street segments in either urban or more suburban/rural places (e.g. downtown, shopping centers, and other clustered business stores) may generate the most property crime, causing these findings. Meanwhile, different subtypes of property crime such as burglary, criminal damage and arson, other theft, theft from a person, and vehicle crime (theft from or of a vehicle) may cause the fewer crime concentrations at large areas with low frequency of property crime.

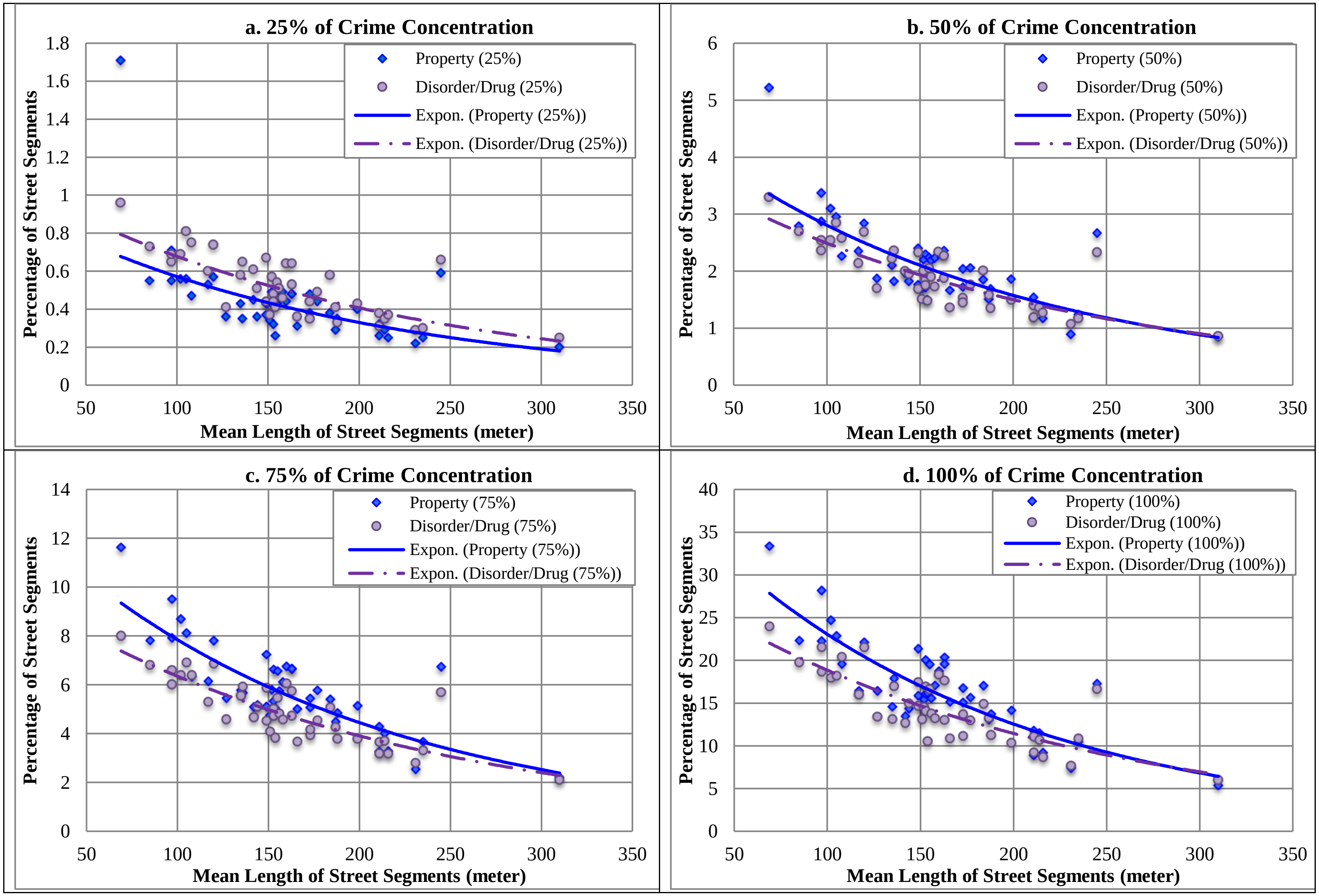

Figure 4. Crime Concentrations of Property and Disorder/Drug Crime for 43 Jurisdictions By Length of Street Segment

To compare crime concentrations across jurisdictions for different categories of crime, Figure 5 charts the generalized Gini coefficients for different crime types across 42 jurisdictions organized by average length of street segment within each jurisdiction. Recall, a generalized Gini coefficient of 0 means that crime is evenly distributed across street segments, while a Gini coefficient of 1 means that crime is maximally disproportionately distributed. According to Figure 5, the range of generalized Gini coefficients show that all crime disproportionally concentrates in very small places (between .869 and .977). Additionally, violence (between .884 and .977), disorder/drug crimes (between .909 and .972), and property crime (between .879 and .972) also highly concentrate in smaller places. The generalized Gini coefficients show the distinctive levels of crime concentration by crime types, which is a similar finding from the analyses of arbitrary cutoffs that violent crime is more spatially concentrates than property crime especially at 75 and 100% of crime concentrations.

Importantly, the Gini calculations could be interpreted as a narrow bandwidth of cumulative crime concentration across jurisdictions and for different crime types because the differences between the maximum (.98) and minimum Gini coefficient (.87) is around .10. Again, .10 is an arbitrary setting for a “narrow bandwidth” and needs further empirical exploration in future studies. However, the findings indicate that the bandwidth of crime concentration appears to be narrow and generally supportive of Weisburd’s law.

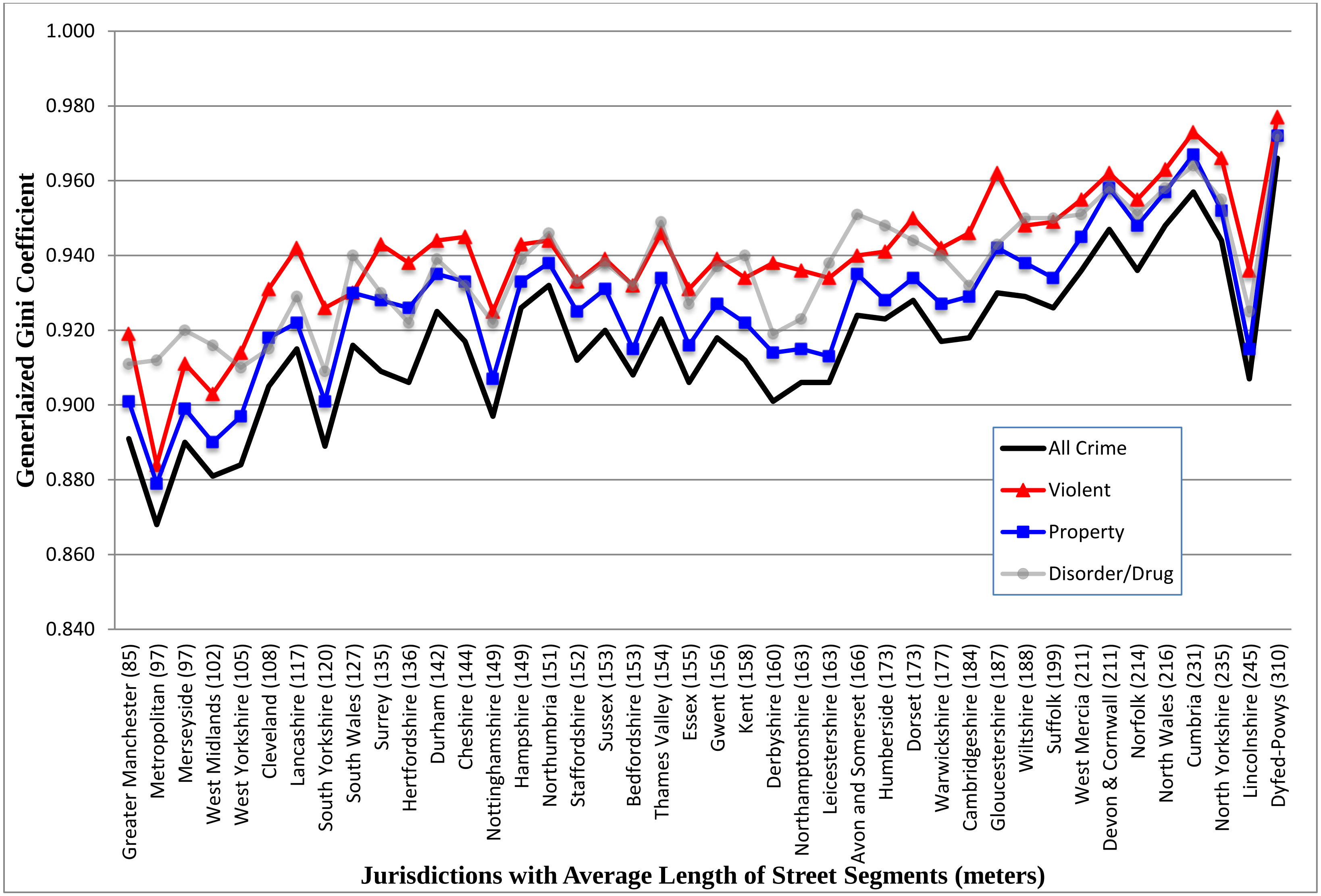

Figure 5. Generalized Gini Coefficients for 42 Jurisdictions By Length of Street Segment (Excluding the City of London)

To summarize these results thus far, there are three important descriptive findings related to crime concentrations across the U.K. First, these findings generally support Weisburd (2015); there is a high level of crime concentrations in jurisdictions, and these concentrations can be seen across multiple jurisdictions within an entire country. However, it appears the crime concentration calculations for 25, 50, 75, and 100% of the crime in England and Wales reveal much higher crime concentrations than Weisburd observed in his sample. Second, the level of crime concentrations vary across crime types, and these variations are significantly different from each other and from all crime combined. Property crime significantly concentrates at much smaller places at 25% concentration, but is more spatially distributed at 100% concentration compared to violent and disorder/drug crime. Violent crime is highly concentrated at 100% concentration compared to property and disorder/drug crime. The level of disorder/drug crime concentrations are somewhere in between property and violent crime. Therefore, the findings of generalized Gini coefficients further support that violent crime is more spatially concentrated than property and disorder/drug crime across jurisdictions. These variations emphasize the importance of not only looking at a larger sample of jurisdictions (as done by Hipp & Kim, 2016), but also examining concentrations across crime types, and across jurisdictions that are structurally different (i.e., have different street segment lengths). Lastly, the bandwidth of crime concentrations (the minimum and maximum crime concentrations across the 42 jurisdictions) could be interpreted as "narrow". This study however, shows that such a "law" of crime concentration is dictated not by a specific principle (or bandwidth), but by an equation for the bandwidth that reflects various factors in that equation.

Crime Concentrations and Urbanization

The above analysis only examines average crime concentrations across jurisdictions for various crime types. Figures 2 – 5 showed interesting variations, especially when considering the average length of street segments across jurisdictions. Specifically, places with longer street segments tend to have higher concentrations of crime. As Hipp and Kim advocate, further analysis of the jurisdictions themselves may reveal additional explanations for the variation in crime concentrations and street segment length. Here we explore two possible measures of urbanization and explanation of crime concentration variation: street segment length and population density.

Street Segment Length

Weisburd (2015) hypothesized that places with longer street segments could also be less urban, and therefore have greater crime concentrations. For example, if jurisdictions with lower population densities tend to have more long street segments, then it may be that longer segment length is what is contributing to higher crime concentrations seen in more rural places. Similarly, if places with greater population density tend to have more short street segments, then it may be that shorter segment length is what is contributing to lower crime concentration calculations seen in more urban places. In other words, urbanized jurisdictions have more street segments with shorter streets, and less urbanized jurisdictions have fewer street segments that are longer.

If crime tends to occur on in particular length of street segments, distributions of short and long length of street segments in each jurisdiction leads to different levels of crime concentrations. Thus, it is important to take length of street segments into consideration when measuring urbanization to understand different levels of crime concentrations across the jurisdictions.

From our averages above, Figures 6, 7, 8, and 9 are expanded graphs which show each of the 43 police jurisdictions in England and Wales according to their mean length of street segments from the shortest to longest and for each level of crime concentration (25, 50, 75, and 100% of crime). The figures confirm previous charts above, and consistently show—with some exceptions—a positive relationship between length of street segments and the level of crime concentration at different percent concentrations (recall, lower percentages mean *higher* crime concentrations). For example, Figure 6 shows that jurisdictions that are considered as more rural such as Dyfed-Powys, North Yorkshire, Cumbria, North Wales, Norfolk, Devon and Cornwall, or West Mercia have longer mean length of street segments (above 200m) and also greater crime concentrations (around between 0.27 and 0.47% of street segments for 25% of all crime) compared to more "urban" jurisdictions with on average shorter street segments, such as the City of London, Greater Manchester, Merseyside, Metropolitan, West Midlands, or West Yorkshire, whose mean segment length is under 110m, with crime concentrations from 0.78 to 1.81% of street segments). These trends are also seen when calculating crime concentrations with 50, 75, and 100% of crime (see Figures 7, 8, and 9). The figures also break down these trends by crime type, which also show similar trends.

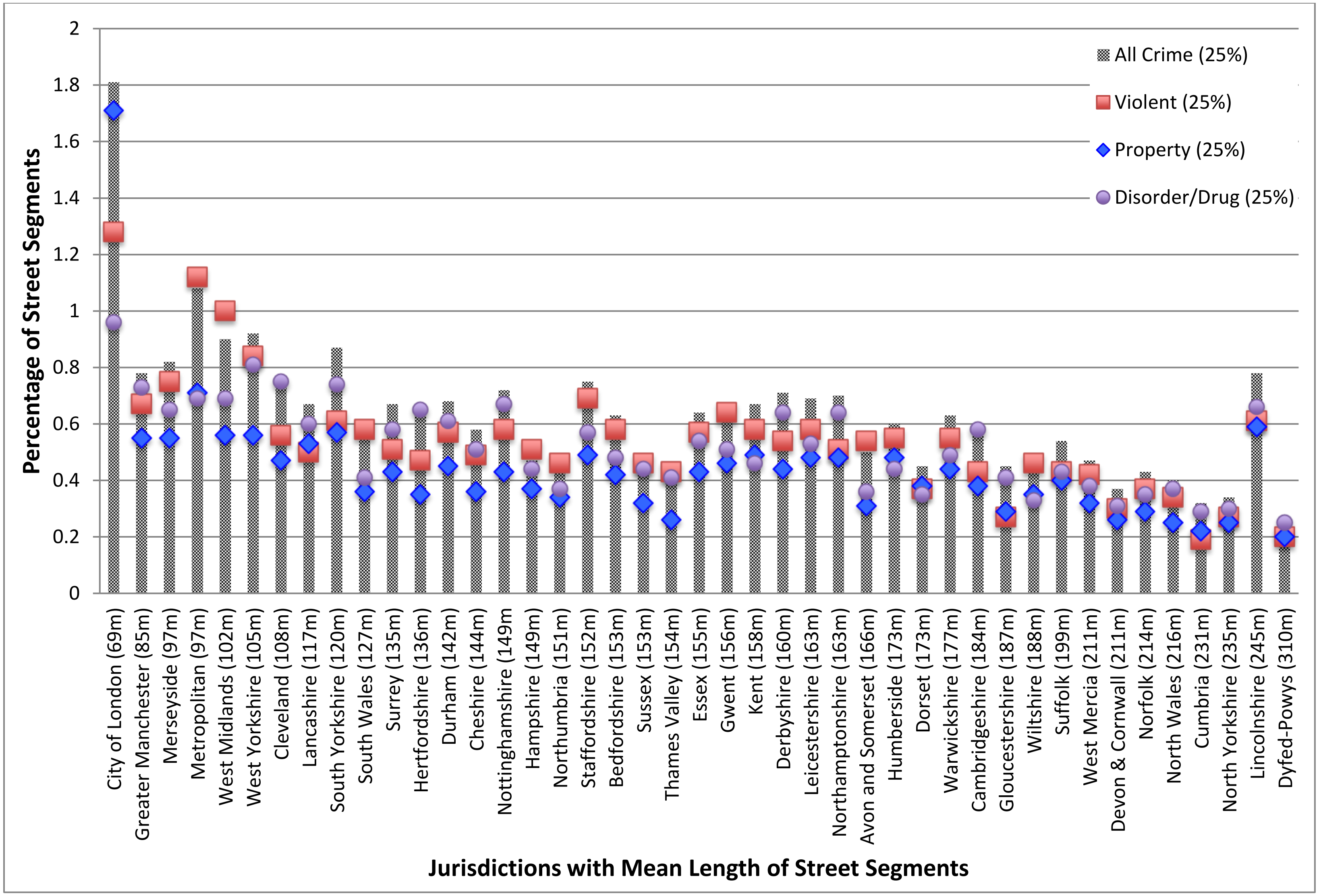

Figure 6. 25% of Crime Concentrations by Crime Types and Mean Length of Street Segments for 43 Jurisdictions

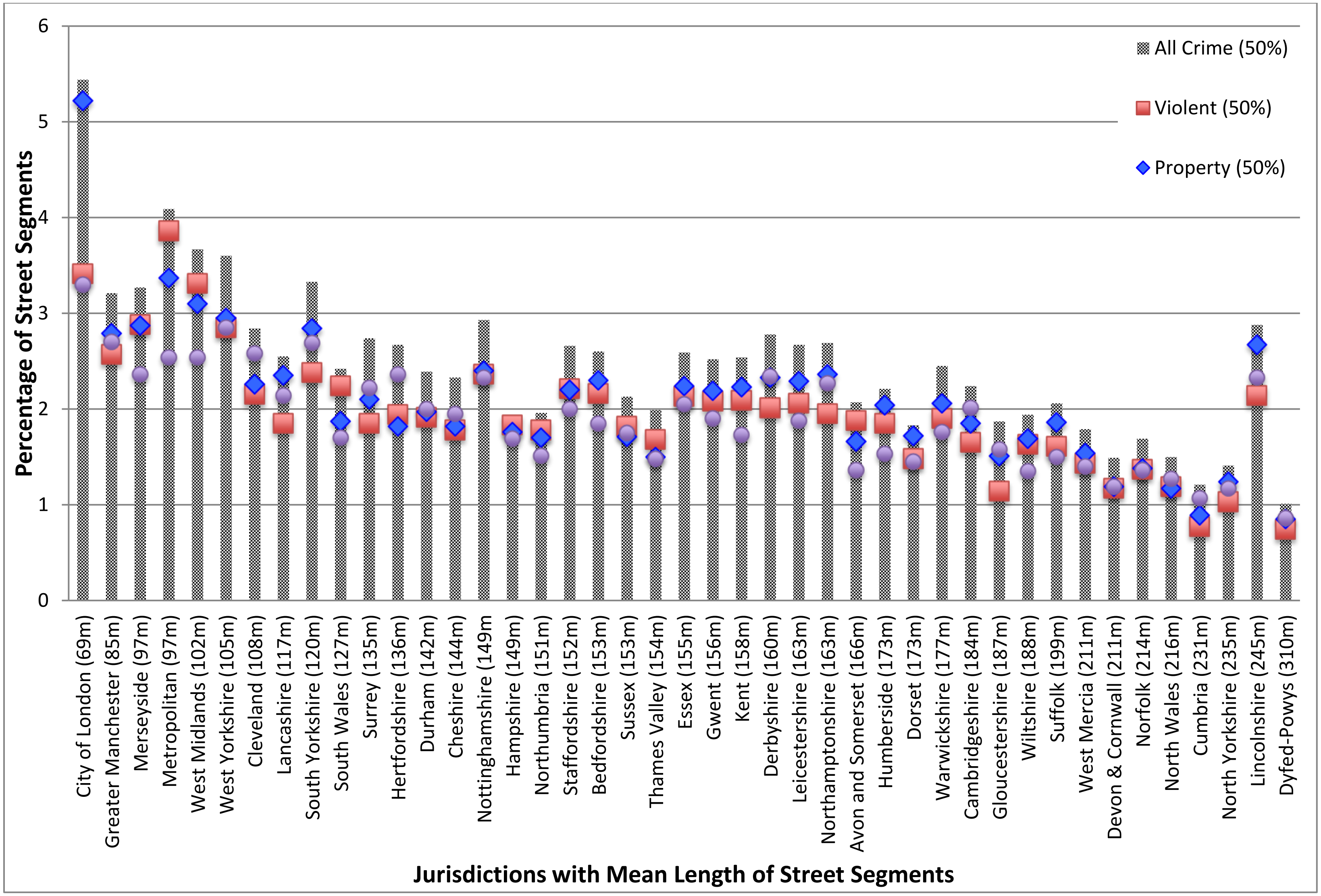

Figure 7. 50% of Crime Concentrations by Crime Types and Mean Length of Street Segments for 43 Jurisdictions

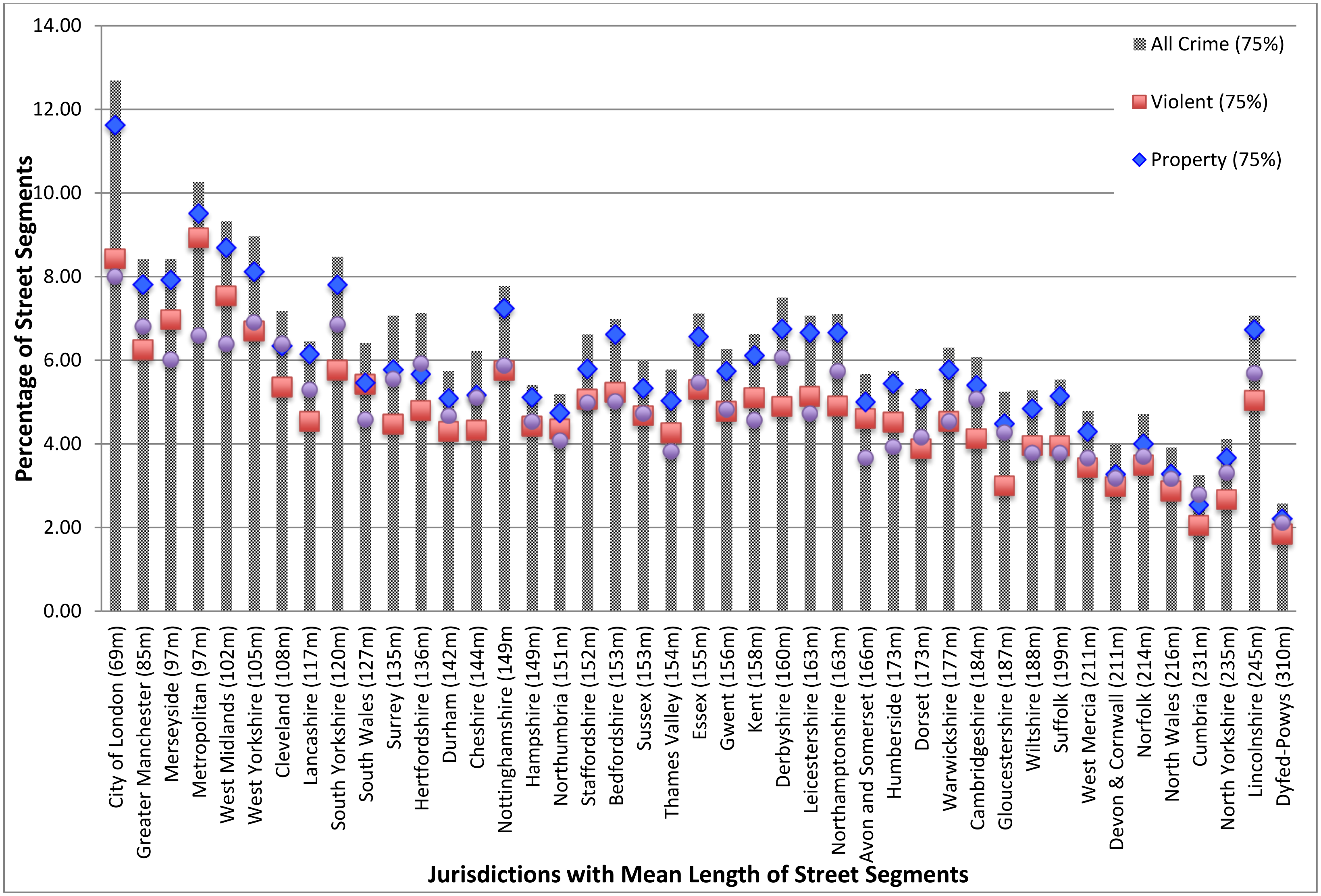

Figure 8. 75% of Crime Concentrations by Crime Types and Mean Length of Street Segments for 43 Jurisdictions

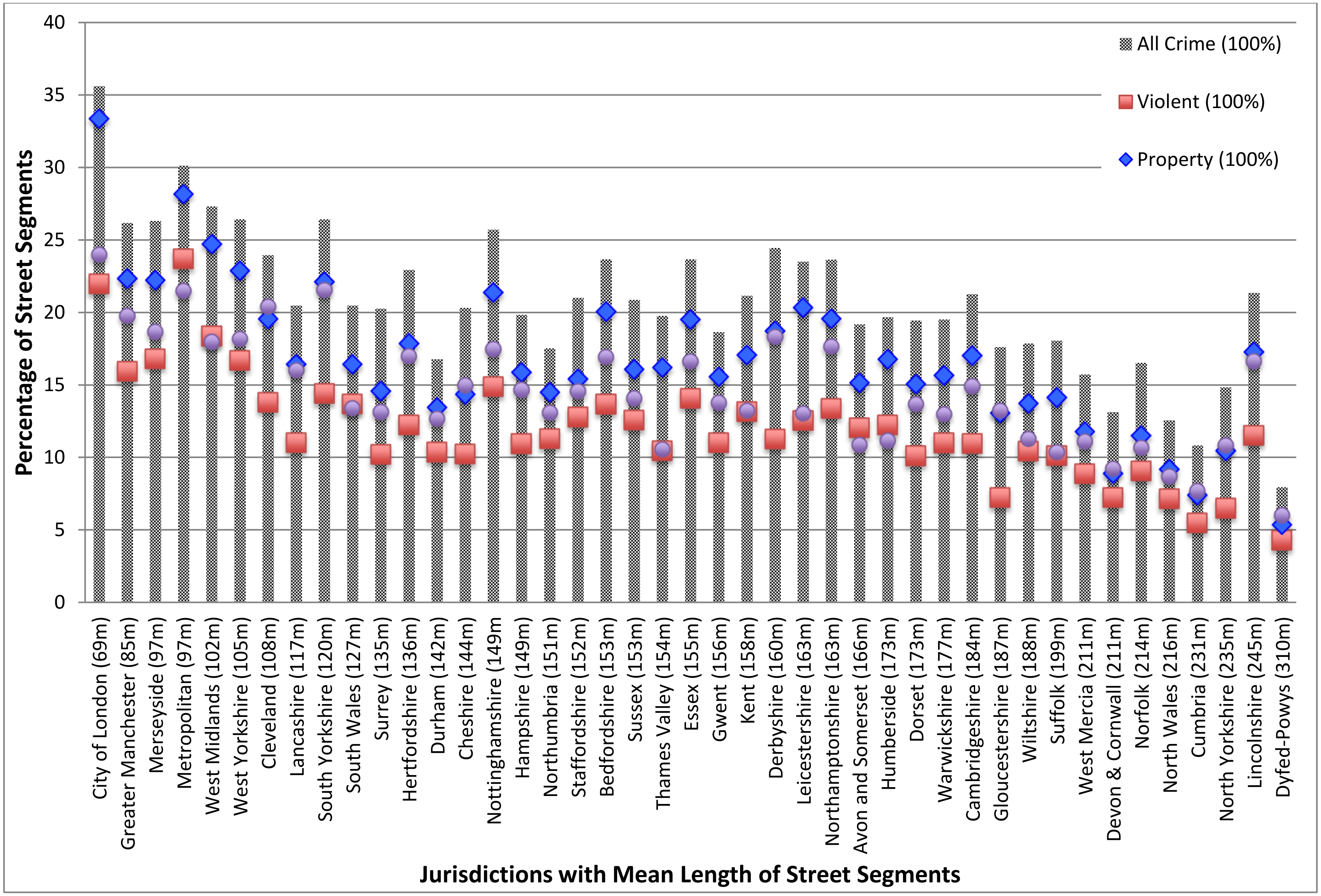

Figure 9. 100% of Crime Concentrations by Crime Types and Mean Length of Street Segments for 43 Jurisdictions

The average street segment length, however, may not adequately characterize the extent of urbanization in these jurisdictions. Some of these jurisdictions are neither completely rural or urban, but are a mixture of urban, suburban, and rural areas with varying street lengths within them. Thus, to analyze the relationship between urbanization (as examined by street segment length) and crime concentrations further, Table 9 shows a statistical distribution of length of street segments with kurtosis and skewness for each distribution. Also shown is the length of street segments for each jurisdiction that fall in the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile with regard to relative size of the street segment (in meters) within the jurisdiction. As a review, Kurtosis is defined as the degree of peakedness of a statistical distribution, indicative of the concentrations around the mean, while skewness is the lack of symmetry of the a frequency distribution.

Table 9. Skewness, Kurtosis, and Distribution of Street Segments (by Percentile) of the 43 Jurisdictions

Police Force	Skewness	Kurtosis	Percentile of length of Street Segments (meters)				
			10%	25%	50%	75%	90%
Avon and Somerset	5	58	28	47	84	165	373
Bedfordshire	5	42	28	48	82	154	310
Cambridgeshire	5	58	29	49	86	168	407
Cheshire	5	65	27	46	80	151	315
City of London	2	14	18	36	59	90	132
Cleveland	9	231	25	41	69	120	208
Cumbria	5	58	26	49	100	244	600
Derbyshire	6	72	30	50	86	164	344
Devon & Cornwall	3	24	27	50	104	242	545
Dorset	4	36	28	49	89	173	378
Durham	8	126	24	39	71	137	299
Dyfed-Powys	4	31	35	70	164	402	758
Essex	5	37	28	48	85	162	335
Gloucestershire	4	29	26	49	93	193	442
Greater Manchester	10	303	23	36	60	100	164
Gwent	6	78	27	43	81	159	341
Hampshire	6	64	28	47	82	154	312
Hertfordshire	5	47	27	46	79	142	247
Humberside	5	49	29	48	83	160	363
Kent	4	34	27	48	87	169	348
Lancashire	6	81	22	36	64	118	239
Leicestershire	6	70	29	50	86	162	336
Lincolnshire	4	22	28	52	102	237	659
Merseyside	7	127	23	40	67	115	191
Metropolitan	8	281	25	43	71	121	198
Norfolk	4	25	24	49	98	221	556
North Wales	5	52	30	55	108	244	520
North Yorkshire	5	45	26	50	101	244	607
Northamptonshire	6	60	29	47	81	156	344
Northumbria	7	90	26	40	72	137	291
Nottinghamshire	5	46	30	50	84	153	296
South Wales	8	109	27	41	73	135	250
South Yorkshire	8	131	28	45	74	129	227
Staffordshire	4	30	26	46	81	157	340
Suffolk	4	24	26	50	97	208	501

Surrey	5	40	26	47	85	156	287
Sussex	5	39	28	49	87	167	332
Thames Valley	5	61	27	47	83	158	328
Warwickshire	6	89	27	49	90	183	412
West Mercia	4	29	29	53	105	232	535
West Midlands	5	52	28	46	75	124	202
West Yorkshire	9	180	24	40	68	117	203
Wiltshire	5	37	28	48	88	182	439
England & Wales (Average)	5	74	27	47	85	170	360

Note: The skewness of 0 and the kurtosis of 3 are considered as normal distribution. The greater number of skewness, the lack of symmetry. The greater number of kurtosis, the greater numbers of outliers, or heavy tails.

Table 9 shows that jurisdictions with high levels of skewness (8 and above) and kurtosis (above 100) (e.g. Cleveland, Durham, Greater Manchester, Metropolitan, South Wale, South Yorkshire, West Yorkshire) have relatively short lengths of street segment (around 200 meters) compared to others jurisdictions with lower levels of skewness and kurtosis (e.g. Devon and Cornwall, Dyfed-Powys, Gloucestershire, Lincolnshire, Norfolk, Staffordshire, Suffolk, West Mercia who average 542 meters at the 90th percentile. This may suggest that there is a correlation between skewness and kurtosis, and that both together can better explain the level of urbanization within jurisdictions if measured by street segment length. Because jurisdictions with high skewness and kurtosis have a large percentage of short segments, we may consider jurisdictions with high skewness and kurtosis as highly urbanized jurisdictions. For example, Greater Manchester—both high values in kurtosis and skewness—is more urbanized jurisdiction than Dyfed-Powys—both lower values in skewness and kurtosis. Nevertheless, it is not necessary to have high kurtosis and skewness to indicate a high probability of urbanization. For instance, although the distribution of street segments across the percentile cuts for the City of London and Greater Manchester are very similar, the City of London (a highly urbanized environment) has much lower kurtosis and skewness compared to Greater Manchester. Perhaps only looking at kurtosis and skewness of a statistical distribution is inappropriate to measure distributions of urbanization. Rather, looking at the different percentiles of the lengths of street segments and both kurtosis and skewness deliver a better understanding of the distribution of varying ranges of street segments and the level of urbanization within these jurisdictions.

Thus, Table 9 also provides the distribution of different lengths of street segments at the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles for each of the 43 jurisdictions. The average length across these percentiles across the jurisdiction is 27, 47, 85, 179, and 360, respectively. Notice that the lengths of street segments between jurisdictions are significantly different at the 75^{th} and 90^{th} percentile (see also Figure 10 below). This indicates that there may be large variation just within the level of urbanization in these jurisdictions. For example, Dyfed-Powys has the longest street segments at the 75^{th} (402 meters) and 90^{th} percentile (758 meters), but it might also be argued to be one of the least urbanized among the 43 jurisdictions. In contrast, Greater Manchester, which has relatively very short length of street segments at the 75^{th} (100 meters) and 90^{th} percentile (164 meters), can be identified as one of the most urbanized jurisdictions in the sample. In this way, comparing different levels of urbanization by looking at 75^{th} and 90^{th} percentile can be useful to classify jurisdictions with regard to their urban-ness, while the length of street segments at 10^{th}, 25^{th}, and 50^{th} percentile are similar across jurisdictions.

The distributions of length of street segments may further explain the different levels of crime concentrations found in previous figures. As seen from Figure 6 to 9, places on average with longer street segments had higher crime concentrations. Figure 10, which shows the distribution of different lengths of street segments from multiple jurisdictions, further describes the different distribution of street segments at 75th and 90th percentile of street segments compared to 10th, 25th, and 50th percentile length of street segments. Taken together these findings indicate that a large distribution of longer street segments mostly impacts levels of crime concentrations. Because jurisdictions consist of more long street segments in general have higher levels of crime concentrations, we must understand why having more long segments leads to high crime concentrations. Thus, analyzing crime occurrence in different street length will account for the viabilities of crime concentration by street lengths.

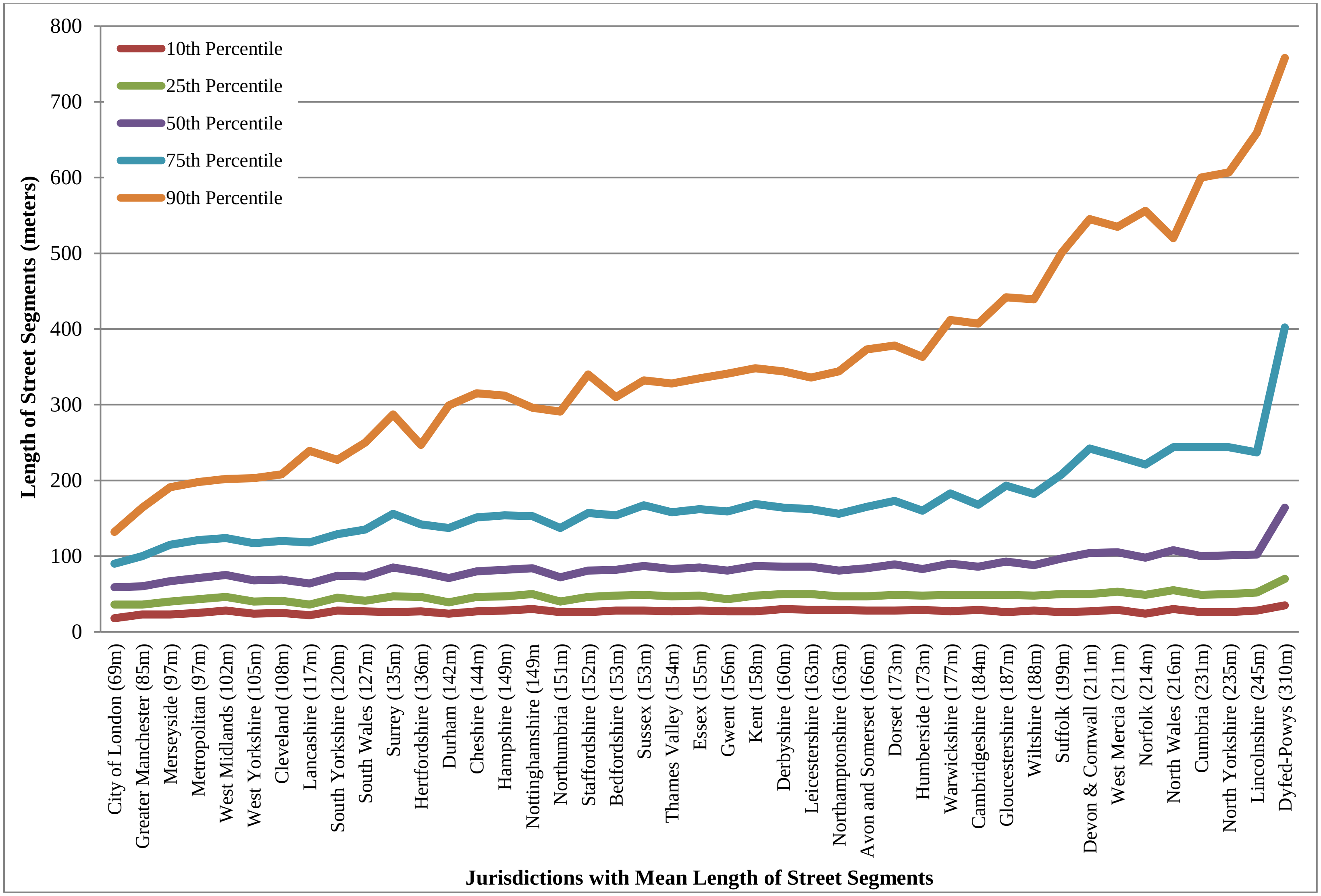

Figure 10. Distribution of Length of Street Segments at 10th, 25th, 50th, 75th, and 90th Percentile Across Jurisdictions

Using the street segment lengths based on the 10th, 25th, 50th, 75th, and 90th percentiles of street length from Table 9, Table 10 shows the percentage of crime incidents that occurred in specific range of street lengths. The length of street segments is set as follows: 1 to 30 meters for 10th percentile of length of street segments, 31 to 60 for 25th percentile, 61 to 120 for 50th percentile, 121 to 240 for 75th percentile, 241 to 480 for 90th percentile, and 481 and above for the rest of street segments. As Table 10 illustrates, the largest proportion of crime incidents occurred on street lengths between 61 and 120 meters (about 37%). The second largest proportion of crime incidents occurred on lengths between 121 and 240 meters (30%). The third largest proportion of crime incidents occurred on street lengths between 31 and 60 meters (17%). In total, these three street length ranges house 84% of all crime in the data. The remaining 16% of crime occurred from 241 and 480 meters (about 11%), 481 meters and above (about 4%), and 1 to 30 meters (about 3%).

Table 10. Distribution of Crime at Different Length of Street Segments (Percentage)

	Length of street segment (meters)						
# of Incidents	1 to 30 (%)	31 to 60 (%)	61 to 120 (%)	121 to 240 (%)	241 to 480 (%)	481 above (%)	Total (%)
1	2	17	36	26	10	8	100
2	2	17	36	28	11	7	100
3 to 5	2	17	37	29	11	5	100
6 to 9	3	17	37	30	10	3	100
10 to 20	3	17	37	31	10	2	100
21 to 40	3	17	37	31	10	2	100
41 to 100	3	17	37	32	10	2	100
101 above	2	15	35	33	12	2	100
Average	2.5	17	36.5	30	10.5	3.9	100

Interestingly, long street segments—above 481 meters—have the second least amount of crime incidents. This means that our earlier hypothesis—that longer street segments have more crime due to their size—may not be warranted. More likely is that crime occurs on a particular type of length of street segments (between 31 to 240 meters). Thus, jurisdictions with long street segments (longer than 240 meters) are likely to have higher crime concentrations not because more crime occurs on longer street segments, but because the crime in these places tend to be concentrated on the small number of shorter street segments. 85% of street segments above 480 meters had no crime crimes, and 14% of street segments had fewer than 10 incidents (see Table 11).

At the same time, such logic does not mean that very small street segments will have high levels of crime. Streets ranging between 1 to 30 meters in our jurisdictions appear to have a smaller proportion of crimes than street segments of 31 to 60 meters. Perhaps, the short street segments between 1 to 30 meters were generated while geoprocessing the street segments for the unit of analysis that highway ramps and interchanges generated the short length of street segments. Table 11 shows that 97% of street segments between 1 and 30 meters have no crime incident.

Perhaps the short and the long street segments are too short or too long to be "activity spaces" (Brantingham et al. 2009; Felson & Boba, 2010) or "behavior settings" (Felson & Boba, 2010; Taylor, 1997; Weisburd et al., 2016). This cannot be discerned here, but is nonetheless an interesting phenomenon that crime occurs on certain lengths of street segments.

Table 11. The Percentage of Crime Occurrence at Different Lengths of Street Segments

# of Incidents	Length of street segment (meters) 1 to 30 (%)	31 to 60 (%)	61 to 120 (%)	121 to 240 (%)	241 to 480 (%)	481 above (%)
0	97	85	75	68	76	85
1	0	3	5	5	4	5
2	0	2	4	4	3	3
3 to 5	1	4	6	8	6	4
6 to 9	1	2	4	5	4	2
10 to 20	1	2	4	5	4	1
21 to 40	0	1	2	2	2	0
41 to 100	0	0	1	1	1	0
101 above	0	0	0	0	0	0
Total	100	100	100	100	100	100

Population Density

Although the findings of crime concentrations at specific lengths of street is significant, street segment length may not be adequate enough in explaining the variation of crime concentrations across these jurisdictions. For instance, as Figures 6, 7, 8, and 9 show, Greater Manchester, Merseyside, and Lincolnshire all have different levels of crime concentrations compared to other jurisdictions, but with very similar mean street segment lengths to other jurisdictions. Merseyside with a population density of 2,167 people per square kilometer has higher crime concentrations at 50% of all crime (3.27% of street segments) than Metropolitan (5.44) with a population density of 5,523 people per square kilometer, even though the mean length of street segments in both jurisdictions is the same (97 meters). Moreover, the population density of Metropolitan is about two times that of Merseyside, which may lend to different levels of crime concentrations. Lincolnshire, with a population density of 124 people per square kilometer, has a lower level of crime concentration at 50% of all crime (2.88) than North Yorkshire (1.41), which has a population density of 97 people per square kilometer. The explanations suggest that jurisdictions with high population density have lower levels of crime concentrations, and lower population density jurisdictions have higher levels of crime concentrations even if the jurisdictions have the similar average street segment lengths, again confirming the urban-suburban-rural differences in crime concentrations.

Thus, another metric of urbanization in addition to street segment length could be population density, which could also explain the variations in crime concentrations across these jurisdictions. Population density and average street segment length in jurisdictions are strongly correlated to each other. Figure 11 shows a noticeable negative exponential relationship between the length of street segments and the population density. The smaller the population density, the longer the street segments in any given jurisdiction, and vice versa. This may also explain why places with high population density also have lower levels of crime concentrations (and thus, why Hibdon, Gill, and Weisburd all found that suburban areas seem to have higher levels of crime concentrations).

Figure 11 also shows that the length of street segments quickly decreases (from 310 to 100 meters) as population density increases (from 50 to 1,000 km^2), but that the length of street segments becomes more stable (around 100 meters) as population density increases from 1,000 to 5,500km^2. The stability of length of street segments above a population density of 1,000 persons per square kilometer may also explain in part the tight bandwidth of crime concentrations. For instance, if we look at the jurisdictions with a population density of over 1,000 people per square kilometer, we may observe a very tight bandwidth because of the diminishing exponential decay of length of street segments, while increasing population density. The large cities (Cincinnati, Seattle, Tel Aviv-Yafo, New York, Sacramento), included in Weisburd (2015) all have very high population densities (average 4,743 people per square kilometer) and also tight bandwidths of crime concentrations (4.2 to 6% of streets hold 50% of crime). Thus, by only looking at major cities, one might *underestimate* the range of crime concentrations that can be found across different types of jurisdictions.

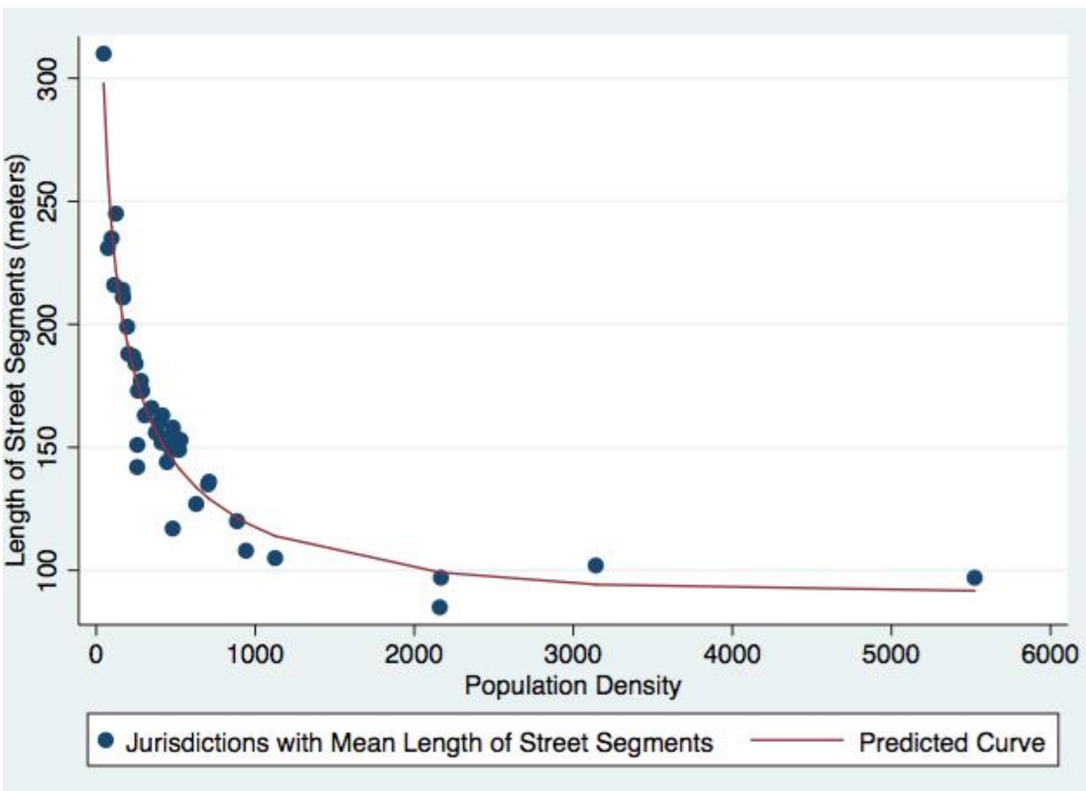

Figure 11. Non-linear Relationship between Length of Street Segments and Population Density (42 Jurisdictions Excluding the City of London)

In summary, these analyses on street segment length and population density provides four important findings. First, the average length of street segments could be a good measure for “urbanization” in order to classify jurisdictions with regard to their crime concentrations. In particular, different lengths of street segments, especially at the 75th and 90th percentiles of relative street lengths can be used to differentiate between highly urbanized and less urbanized jurisdictions. Overall, it appears that jurisdictions with longer street segments are less urbanized, and those with shorter street segments are more urbanized.

Second, even though places with higher crime concentrations usually have longer street segments, crime is still more likely to occur on short street segments (between 31 to 240 meters) rather than longer ones (above 241 meters). Because more urbanized jurisdictions have more short street segments, the level of crime concentration in the jurisdictions are lower due to greater spatial distribution of crime at places than the jurisdictions with more long street segments.

Third, population density is also a convenient measure of urbanization for the study of crime concentration. Population density can help to further explain the variation of crime concentrations between jurisdictions that have similar average street segment lengths.

Finally, there is a negative exponential relationship between the length of street segments and population density, which further reinforces the idea that more urbanized, population-dense places have lower crime concentrations (although, notably, the concentration is still relatively high). Moreover, the exponential relationship between density and street segment length could help to explain the tight bandwidth of crime (from 0.27 to 1.08% of street segments for 25% concentration and from 1.01 to 4.09% for 50% of all crime).

Variations of Crime Concentrations across Jurisdictions: Regression Analysis

In addition to population density and street segment length, there may be other factors that explain variations in crime concentrations across the 43 jurisdictions in England and Wales, such as the social characteristics of places. To further explore these variations, correlations between crime concentrations calculations were run against a variety of explanatory variables: the mean length of street segments (LSS), population density, lone parent (the ratio of lone parents with dependent children), unemployment (the percentage of people without a job who are available to work), non-white (the ratio of non-whites to white), jobs density (the ratio of jobs in an area divided by the total population aged 16-64), and Gross Disposable Household Income (GDHI) per head index (the amount of money that the individuals in the household sector have available for spending or saving after income distribution measures).

Table 12 displays the bivariate correlation results (excluding the City of London) of each of these variables with each crime concentration for 25, 50, 75, and 100% of the crime. Generally, LSS, population density, lone parent, unemployment, and non-white population are all statistically significant ($p<.01$), except jobs density and GDHI per head index are insignificant at different percentages of concentrations calculations and types of crime. Table 12 also shows that social and physical characteristics of jurisdictions are significantly correlated with levels of crime concentrations.

Table 12. Correlations Coefficients Values (Spearman's rho) between Crime Types and Characteristics of Jurisdictions (42 Jurisdictions Excluding the City of London)

Crime Type	Variable	25% of crime concentration	50% of crime concentration	75% of crime concentration	100% of crime concentration
		r_s	r_s	r_s	r_s
All Crime					
	LSS	-0.70***	-0.73***	-0.75***	-0.72***
	Population Density	0.74***	0.81***	0.86***	0.85***
	Lone parent	0.65***	0.61***	0.59***	0.58***
	Unemployment	0.64***	0.58***	0.54***	0.54***
	Non-white	0.42**	0.53***	0.60***	0.66***
	Jobs density	-0.42**	-0.36*	-0.33*	-0.32*
	GDHI per head index	-0.41**	-0.32*	-0.26	-0.25
Violent					
	LSS	-0.69***	-0.76***	-0.76***	-0.74***
	Population Density	0.74***	0.83***	0.86***	0.84***
	Lone parent	0.69***	0.72***	0.69***	0.71***
	Unemployment	0.68***	0.68***	0.65***	0.66***
	Non-white	0.36*	0.44**	0.51***	0.52***
	Jobs density	-0.54***	-0.52***	-0.50***	-0.49**
	GDHI per head index	-0.44**	-0.42**	-0.37*	-0.36*
Property					
	LSS	-0.60***	-0.67***	-0.68***	-0.69***
	Population Density	0.63***	0.74***	0.79***	0.82***
	Lone parent	0.59**	0.64***	0.60***	0.62***
	Unemployment	0.64***	0.65***	0.60***	0.58***
	Non-white	0.36*	0.50***	0.58***	0.66***
	Jobs density	-0.47**	-0.44**	-0.39*	-0.36*
	GDHI per head index	-0.43**	-0.42**	-0.34*	-0.30
Disorder/Drug					
	LSS	-0.72***	-0.77***	-0.77***	-0.73***
	Population Density	0.74***	0.78***	0.81***	0.79***
	Lone parent	0.61***	0.60***	0.59***	0.62***
	Unemployment	0.60***	0.57**	0.55***	0.56***
	Non-white	0.46**	0.48**	0.52***	0.47**
	Jobs density	-0.31*	-0.32*	-0.31*	-0.36*
	GDHI per head index	-0.36*	-0.32*	-0.28	-0.28

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Note: Because of the presence of heteroskedasticity, outliers, and non-linear relationship, Spearman's rho used to measure rank correlation. LSS means Mean length of Street Segments

Here, LSS, population density, lone parent, unemployment, and non-white ratio are all significantly correlated with varying crime concentrations calculations. The population density statistically significantly correlates with the level of crime concentration ($r_s =$ .63 to .87, p<.001). The positive correlations suggest that jurisdictions with high population density tend to have higher percentages of street segments (recall, high percentages of street segments means low crime concentrations). There is a negative correlations between LSS and the level of crime concentration ($r_s =$ -.60 to .-77, p<.001), which means jurisdictions with longer LSS tend to have higher crime concentrations. These statistical outcomes support the descriptive statistics of the relationship between crime concentrations and urbanization, which means increasing in urbanization rate correlates with lower levels of crime concentrations. Moreover, social characteristics of jurisdictions (i.e. lone parent, unemployment, and non-white) also are positively correlated. Both jobs density and GDHI per head index negatively correlate with law of crime concentrations (p<.05), except GDHI per head index is only statistically significantly correlate with violent crime at all the crime concentrations calculations. Because there is a negative relationship, the increasing in jobs density and GDHI per head index results in higher levels of crime concentrations.

For this reason, a correlation coefficients test is run to detect high multicollinearity prior to the multivariate regression. To take into consideration violations of normality such as outliers from the population density and non-linear relationships between length of street segments and population density (see Table 12), this study uses Spearman rank-order correlation coefficient to measure the strength and direction of association between variables and sets .80 as the threshold value for statistically significant causes of multicollinearity.

Table 13. Correlations Coefficients Values (Spearman's rho) between Characteristics of Jurisdictions (42 jurisdictions Excluding the City of London)

	1	2	3	4	5	6
1. Length of Street Segments						
2. Population Density	-0.93*					
3. Lone Parent	-0.75	0.65				
4. Unemployment	-0.60	0.52	0.89*			
5. Non-white	-0.40	0.57	0.10	0.00		
6. Jobs density	0.32	-0.32	-0.61	-0.72	0.21	
7. GDHI per head index	0.30	0.18	-0.65	-0.81*	0.18	0.68

* $p < 0.001$

According to Table 13, there is a strong negative correlation between length of street segments and population density, which is statistically significant, $r_s = -.93$, $p < .001$. The negative correlation is strong: as described in the descriptive analyses, jurisdictions with high population density have more short length of street segments, and jurisdictions with low population density have more long street segments (see Figure 11). As shown in Table 13, unemployment rate and lone parent ratio have a strong positive correlation ($r_s = .89$, $p < .001$). Unemployment also has a strong negative correlation with GDHI per head index ($r_s = -.81$, $p < .001$). Based on entry method analysis, the three variables (lone-parent, unemployment, and GDHI per head index) did not have significant partial effect in the full model (including LSS, non-white, and jobs density) with regard to predicting the level of crime concentration across crime types. Thus, the statistically insignificant three variables were removed from the multivariate regression, and LSS, non-white, and jobs density were selected for the multivariate regression analyses. LSS is selected over population density for multiple linear regression analysis because the relationship between the level of crime concentration and the population density is a curvilinear (see Figure 12).

The results of the multivariate regression analyses for crime concentrations based on 42 jurisdictions (excluding the City of London) are shown in Table 14. The results of regression indicate that the variables (LSS, nonwhite, jobs density) significantly predict the level of all crime, violent, and property crime concentration across different percent concentrations calculations. The effect of LSS is statistically significant and its coefficient is negative (β=-.36 to -.46, p<.05), which would indicate that longer length of street segments is related to smaller percentage of street segments (high crime concentrations). The non-white variable is highly positively related to crime concentrations (β=.40 to .52, p<.05) that higher non-white ratio is related to higher percentage of street segments (low crime concentrations). Jobs density is significant and its coefficient is negative (β=-.20 to -.39, p<.05) indicating that the greater the proportion of jobs density, the lower percentage of street segments (high crime concentrations). With respect to the level of disorder/drug crime concentrations, LSS had a significant partial effect in the full model for disorder/drug crime concentrations (β=-.56 to -.64, p<.05), while non-white and jobs density did not have a significant partial effect at certain percentage of concentrations calculations. In terms of multicollinearity, the Variance Inflation Factor (VIF) is small (1.43) enough to not concern strong correlations between predictors; we set “rule of thumb” of 5 for high correlations. Because the condition number is 2.01 (the rule of thumb is 15 for this analysis), multicollinearity is not considered. As a result, multivariable regression analyses show different associations between crime concentrations and characteristics of jurisdictions. In other words, the findings represent that the level of crime concentration varies, and the variability of crime concentrations can be predicted by different characteristics of jurisdictions.

Table 14. Multivariate Regression of Crime Concentration (42 Jurisdictions Excluding the City of London)

Crime Types	25% of Crime Concentration			50% of Crime Concentration			75% of Crime Concentration			100% of Crime Concentration		
Variable	*B*	*Robust SE*	*β*	*B*	*Robust SE*	*β*	*B*	*Robust SE*	*β*	*B*	*Robust SE*	*β*
All Crime												
LSS	-0.002	0.0006	-0.46**	-0.008	0.0020	-0.53**	-0.019	0.0045	-0.55***	-0.058	0.0129	-0.57***
Jobs density	-0.606	0.2356	-0.31*	-1.909	0.7884	-0.26*	-3.852	1.6646	-0.22*	-9.935	4.3002	-0.20*
Non-white	0.008	0.0026	0.40**	0.031	0.0073	0.42***	0.078	0.0149	0.43***	0.215	0.0406	0.42***
Adjusted R^2		0.68			0.76			0.80			0.79	
F		31.85			47.04			63.70			69.34	
Violent												
LSS	-0.002	0.0005	-0.41**	-0.006	0.0016	-0.49***	-0.015	0.0035	-0.51***	-0.037	0.0075	-0.48***
Jobs density	-0.660	0.2283	-0.33**	-2.014	0.6785	-0.30**	-4.279	1.4408	-0.29**	-11.009	3.4371	-0.28**
Non-white	0.010	0.0031	0.50**	0.033	0.0089	0.48**	0.072	0.0181	0.48***	0.204	0.0479	0.52***
Adjusted R^2		0.73			0.80			0.83			0.83	
F		25.41			36.25			42.72			53.21	
Property												
LSS	-0.001	0.0004	-0.36*	-0.006	0.0020	-0.44**	-0.017	0.0046	-0.48**	-0.050	0.0115	-0.49***
Jobs density	-0.493	0.1826	-0.39*	-2.316	0.7557	-0.37**	-5.093	1.7017	-0.30**	-13.542	4.1140	-0.27**
Non-white	0.005	0.0020	0.40*	0.028	0.0064	0.43***	0.083	0.0147	0.48***	0.266	0.0362	0.51***
Adjusted R^2		0.60			0.72			0.78			0.83	
F		22.21			41.67			62.08			97.93	
Disorder/Drug												
LSS	-0.002	0.0005	-0.56**	-0.007	0.0017	-0.62***	-0.017	0.0038	-0.64***	-0.046	0.0113	-0.57***
Jobs density	-0.313	0.2035	-0.19	-1.035	0.6609	-0.19	-2.380	1.4687	-0.18	-9.889	4.5275	-0.24*
Non-white	0.003	0.0019	0.21	0.012	0.0056	0.21*	0.031	0.0118	0.23*	0.117	0.0344	0.28**
Adjusted R^2		0.55			0.63			0.68			0.66	
F		24.05			33.93			46.39			55.58	
VIF		1.43										
Condition number												

* $p < 0.05$; **$p < 0.01$; *** $p < 0.001$

Note: Robust regression is used to downplay the influence of outliers

The prediction of crime concentrations with the variables is statistically more significant at higher levels of crime concentration calculation (75% and 100% compared to 25% and 50%) because the predictions of statistical significance of all variables continuously increasing. For example, LSS is more statistically significantly for property crime at higher concentrations: 25% ($p<0.05$), 50% ($p<.01$), 75% ($p<.001$), and 100% ($p<.001$). Although non-white and jobs density did not have a significant partial effect in the full model of disorder/drug crime concentrations, both predictors follow the similar trend that the statistical significance increases and results in significant partial effects for 100% crime concentration calculations. The pattern could explain the descriptive analyses findings—changes in crime concentrations by crime types at 25, 50, 75, and 100% crime concentrations calculations (see Figures 2, 3, and 4)—that the predictors more strongly predict the higher crime concentrations calculations. In other words, there might be other variables significantly influencing the level of crime concentration at smaller crime concentration calculations especially at 25%. In fact, the statistical significance of LSS for property crime prediction at 25% of crime concentration is the smallest value among the other crime types ($p=.49$), which means other factors (e.g. high commercial business districts and shopping malls) could explain the causes of high property crime concentrations at very small places.

While multiple linear regression analyses predict levels of crime concentrations from the social and physical characteristics of the jurisdictions, the linear regression analyses are limited to explaining the tighter bandwidth of crime concentrations. According to the descriptive analyses, this paper shows a tight bandwidth even though the length of street segments of each jurisdiction significantly differs from the others. There may be a non-linear relationship between crime concentrations and population density, which could explain the tighter bandwidth. Figure 12 shows the relationship between population density and the percentage of street segments that have 50% of all crime. Here, one sees a negative exponential increase in the amount of street segments with 50% of the crime, but with gradual decreases in magnitude as population density increases, especially after 1,000 people per square kilometer.

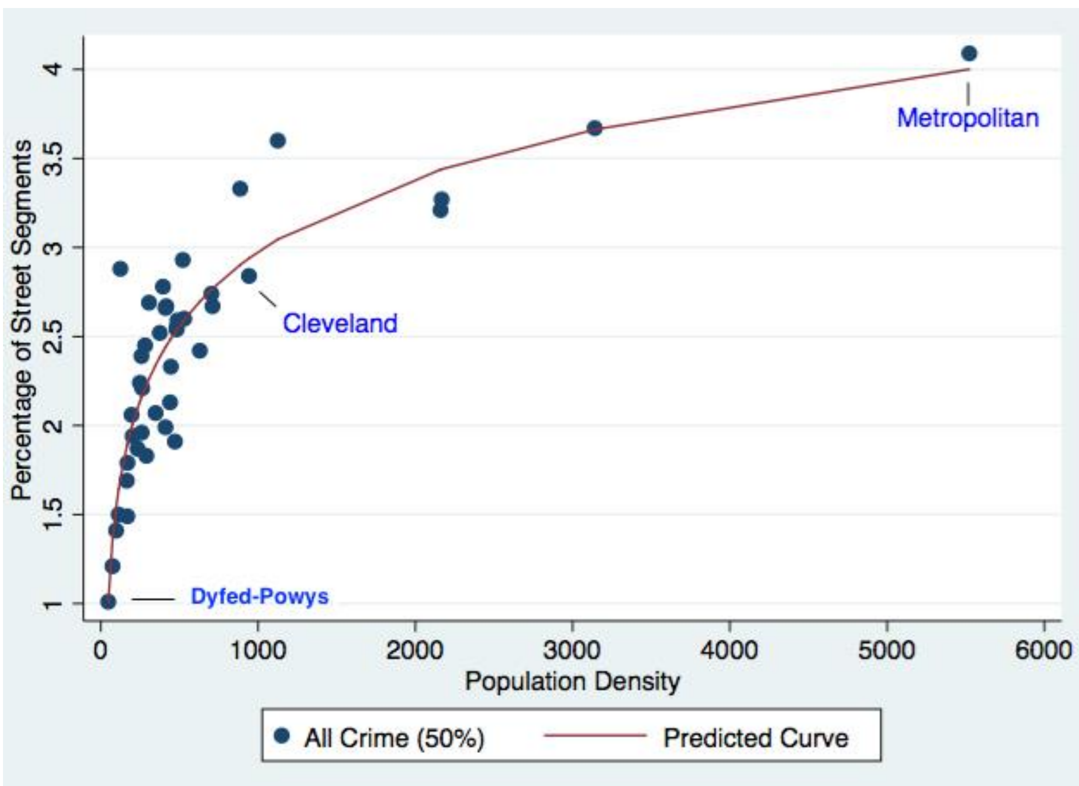

Figure 12. Non-linear Relationship between All Crime Concentrations and Population Density at 50% of Crime Concentration (42 jurisdictions Excluding the City of London)

The relationship between population density and crime concentrations in Figure 12 could in part explain why one might believe there is a law of crime concentration when evaluating more highly populated places. Especially, when population density reaches 1,000 people per square kilometer, the increases in the percentage of street segments gets smaller and results in the tighter bandwidth. As Figure 12 shows, for example, Metropolitan has only one percent more street segments (about 4%) compared to Cleveland (about 3%) even though population density of Metropolitan (5,523 km^2) is about six times greater than Cleveland (942 km^2). In contrast, the percentage of street segments of Cleveland (about 3%) is three times more than Dyfed-Powys (about 1%). In this perspective, the tighter bandwidth (4.2 to 6% of streets for 50% of crime) of the large cities (Cincinnati, Seattle, Tel Aviv-Yafo, New York, Sacramento), which were included in Weisburd's crime concentration research, is due to the high population density (average 4,743 km^2); the average population density of the UK is 383 km^2).

To test whether population density predicts the level of crime concentration, a negative exponential regression analysis between population density and level of crime concentration regression analysis is used. Logarithmic transformation of the model was run to yield the linear regression to test the significance of population density on crime concentrations. Table 15 shows the results of the multivariate regression analyses for crime concentrations based on 42 jurisdictions (excluding the City of London).

Table 15. Multivariate Regression of Crime Concentration (42 Jurisdictions Excluding the City of London)

Crime Types	25% of Crime Concentration			50% of Crime Concentration			75% of Crime Concentration			100% of Crime Concentration		
Variable	*B*	*Robust SE*	*β*	*B*	*Robust SE*	*β*	*B*	*Robust SE*	*β*	*B*	*Robust SE*	*β*
All Crime												
Pop. density	0.116	0.025	0.63***	0.496	0.082	0.71***	1.236	0.189	0.74***	3.404	0.631	0.71***
Jobs density	-0.485	0.194	-0.25*	-1.401	0.611	-0.19*	-2.650	1.333	-0.15	-7.372	4.152	-0.15
Non-white	0.004	0.002	0.20	0.014	0.006	0.19*	0.036	0.015	0.20*	0.111	0.052	0.22*
Adjusted R^2		0.72			0.81			0.84			0.80	
F		56.26			106.48			98.22			45.32	
Violent												
Pop. density	0.117	0.022	0.61***	0.447	0.063	0.70***	1.041	0.137	0.73***	2.474	0.320	0.67***
Jobs density	-0.503	0.184	-0.25*	-1.466	0.501	-0.22**	-3.062	1.044	-0.21**	-8.282	2.710	0.21**
Non-white	0.006	0.002	0.28*	0.016	0.006	0.24*	0.035	0.012	0.23**	0.117	0.034	0.30**
Adjusted R^2		0.79			0.87			0.89			0.88	
F		44.20			99.03			133.61			127.56	
Property												
Pop. density	0.060	0.020	0.50**	0.366	0.083	0.61***	1.056	0.197	0.64***	3.022	0.540	0.62***
Jobs density	-0.430	0.161	-0.34*	-1.918	0.611	-0.30**	-4.036	1.398	-0.23**	-11.048	3.742	-0.22**
Non-white	0.003	0.002	0.24	0.015	0.006	0.23*	0.048	0.015	0.27**	0.171	0.043	0.33***
Adjusted R^2		0.62			0.76			0.82			0.85	
F		33.73			93.97			98.63			97.20	
Disorder/Drug												
Pop. density	0.103	0.024	0.67***	0.392	0.078	0.75***	0.972	0.181	0.78***	2.747	0.555	0.71***
Jobs density	-0.248	0.180	-0.15	-0.761	0.564	-0.14	-1.669	1.251	-0.13	-7.760	3.936	-0.19
Non-white	0.000	0.002	0.03	0.000	0.007	0.00	0.001	0.016	0.01	0.032	0.043	0.08
Adjusted R^2		0.55			0.64			0.69			0.68	
F		22.59			29.26			33.63			44.16	
VIF		1.43										

* $p < 0.05$; **$p < 0.01$; *** $p < 0.001$

Note: Robust regression is used to downplay the influence of outliers. Population density is log transformed.

In the UK, jurisdictions with high population density, lower jobs density and high ratio of non-white to white have lower level of crime concentrations. The results of the regression analysis shown in Table 15 indicate that population density, jobs density, and the proportion of non-white residents significantly predict the level of violent and property crime concentration calculations across different proportions of crime included in those calculations, except non-white for 25% of property crime concentration. The effect of population density is statistically significant and its coefficient is positive (β=.50 to .78, p<.01) across all different types of crime at different percent concentrations of crime, which would indicate that higher population density is related to larger percentage of street segments (low crime concentrations). However, jobs density and non-white are only significant predictors for specific crime types at certain percent of crime. Jobs density (β=-.19 to -.34, p<.05) predicts crime concentrations for all crime, violent, and property across different percent concentrations calculations, except for 75 and 100 percent of all crime. The non-white variable is positively related to crime concentrations (β=.19 to .33, p<.05) for all crime, violent, and property crime at different percent of crime, except 25% for all crime and property crime.

On the other hand, non-white is insufficient to explain the property crime concentration at 25% of crime, because the small number places with high property crimes could be shopping malls where weakly relate to racial classification. Rather, the top 25% of property crime at much smaller places could be much associated with criminal opportunities in particular situations. From this perspective, variables for theories of crime concentration at the micro geographic levels can better predict the level of property crime concentration at the top 25% of crime where in relatively much smaller places than 50, 75, and 100% of crime concentrations calculations. In addition, the higher significant collective effect between the independent variables and levels of crime concentrations at the high proportion of crime amounts, (75% and 100% of crime) than low levels (25% and 50%) supports the idea that crime concentrations vary with population density. These analyses also seem to indicate that not only do crime concentrations vary across jurisdictions, but they vary because of the variation in human ecology.

CHAPTER FIVE: DISCUSSION AND CONCLUSION

This paper assesses whether the law of crime concentration is generalizable to various places, and if variation is found in crime concentrations, what explains those variations. This comprehensive analysis of crime concentrations in England and Wales reveals important findings for Weisburd's Law and Crime Concentration. Indeed, there are high crime concentrations across 43 jurisdictions examined, generally supporting Weisburd's ideas. However, the overall level of crime concentration is higher than the Weisburd's findings, likely because the large size of police jurisdictions in the UK that include longer street segments and lower population density, which can lead to higher crime concentrations. Additionally, although variations of crime concentrations across the 43 jurisdictions fall within a narrow bandwidth, there are important variations that can be explained by street segment length as well as socioeconomic characteristics. Thus, this study finds that Weisburd's law is less a set-in-stone principle or fact, and more an equation to be developed.

More specifically, this study also finds noticeable variations in crime concentrations for specific types of crime. For example, property crime is more spatially concentrated than violent and disorder/drug crime at 25% concentration. Violent crime is more spatially concentrated at 75% and 100% of crime compared to property and disorder/drug. Disorder/drug crime concentrations is somewhere in between property and violent crime. This may be the case that highly clustered commercial business districts and shopping malls generate the top 25% of property crime (e.g., shoplifting), while the rest of the property crimes (e.g., burglary, vehicle crime, criminal damage and arson) are less concentrated. In contrast, violent crimes (e.g., robbery, violence and sexual offences) are generally highly clustered in residential areas and on street or public transportation where highly cluster than burglary, vehicle crime, and criminal damage and arson. This lends more support to the idea of conceptualizing Weisburd's law as an equation and is aligned with place-based theories of crime. Routine activity and environmental theory would explain the variability of crime concentrations because some places have greater (or fewer) opportunities for certain types of criminal activities. For example, there are only about 9,000 people live in the City of London, but 513,000 people are employed.[7] The primary central business district of London (high employment) has created unique environments and created the unique crime opportunities compared to the rest of jurisdictions. In the City of London, there was high level of property crime concentrations across 25, 50, 75, and 100% of crime concentration calculations, whereas other jurisdictions have high violent crime concentration at 50, 75, and 100%. Likewise, crime could be much more associated with human activities and social attributes of places. In fact, levels of crime concentrations are similar among places with similar social characteristics. The City of London (5.4% street segments for 50% all crime) has an almost identical level of crime concentration to New York City in Weisburd's study (5.5% street segments for 50% of all crime). That is perhaps because both places have

[7] City of London https://www.cityoflondon.gov.uk/business/economic-research-and-information/Pages/economic-statistics.aspx

similar social environments that attract crimes even though the physical characteristics of places are different (e.g., size, climate, and location).

This study also finds that the level of crime concentration varies according to two measures of urbanization—street segment length and population density, which are negatively correlated to each other. In this study, more urban jurisdictions with more short-length street segments (between 31 to 240 meters) and higher population densities (above 1,000 km^2) have *lower* crime concentrations (i.e., crime is more dispersed across these segments). Less urbanized jurisdictions tend to have more long street segments (above 241 meters), lower population density (less than 1,000 km^2), and *higher* crime concentrations (more of that jurisdictions crime is concentrated in a small number of street segments. Because crime tends to occur on certain street segments lengths (31 to 240 meters), jurisdictions with varying spatial distributions of more long or short street segments result in different levels of crime concentrations across jurisdictions. Overall, less urbanized jurisdictions have high levels of crime concentrations, and more urbanized jurisdictions have lower levels of crime concentrations. Again, it is important to note that different social factors can influence where crimes occur on specific places among similar length of street segments within a jurisdiction and similar population density across jurisdictions.

Additionally, the results of the multiple regression analyses indicate that certain social and physical characteristics of jurisdictions collectively predict the level of crime concentration in those jurisdictions for different types of crime and at different crime concentration calculations (25%, 50%, etc.). This finding suggests that the law of crime concentration is not a natural phenomenon, rather social phenomena that crimes relate to social and physical environments. The negative exponential relationship between population density and crime concentrations for jurisdictions can better explain the variations and the tight bandwidth of crime concentrations found by Weisburd (2015). This finding indicates that the law of crime concentration may be most salient when examining larger, more populated cities (in particular those with over 1,000 people per square kilometer). These findings more generally supports previous findings that less urbanized places (or smaller cities) have high crime concentrations (Gill et al., 2017; Weisburd, 2015), and why the inclusion of certain street segments in the calculation of crime concentration may increase or decrease crime concentrations (Hipp & Kim, 2016).

Taken together, these results enable further understanding of why jurisdictions vary in their crime concentrations. If a law of crime concentration exists, it is because of the strong relationship between crime and human environments, rather than as an unconditional rule in an of itself. Perhaps opportunities for criminal activities are higher in urbanized places because these places have more short street segments that have greater population density which provide more "behavior settings" (Barker, 1968; Wicker, 1987) and "activity spaces" (Felson & Boba, 2010) for crime. Also, there are more convergences of motivated offenders, a suitable target, and a lack of guardianship (Cohen and Felson, 1979) in urbanized places, which seemingly paradoxically lead to spatially wider distributions of crimes (e.g., low crime concentrations). In comparison, crime is less likely to occur on long street segments, which may present fewer opportunities for these settings and spaces. Thus, different length of street segments and population density, which are formed by human behavior within human settings, influence the opportunity structures for crime, thereby creating different geographic patterns of crime.

Such ideas need further testing but would reinforce theories such as environmental criminology, crime pattern theory, routine activities theories or even social disorganization perspectives that indicate that physical, social, economic, cultural or demographic characteristics could affect how crime concentrates.

In addition to criminological theories of place, agglomeration economic theory may also explain the law of crime concentration. People tend to cluster in order to facilitate economic activities, which leads to more crime occurring in urban areas. This may explain why places in which economic activities are highly clustered also have high levels of crime concentration in more rural areas. On the other hand, wider distributions of economic and criminal activities—which can occur in urban environments—may lead to low level of crime concentration. Scholars have argued that economic systems have a crucial impact on city forms and their social geography (Knox & Pinch, 2014:17), which in turn link crime patterns at places with variables such as jobs density. Furthermore, social geography emphasizes that human geography reflects economic, demographic, cultural, structural, and political aspects of places (Knox & Pinch, 2014), which also could explain the law of crime concentration.

There are a number of limitations to this study, some of which were raised by Hipp and Kim and Weisburd. First, there are some limitations related to the geographic area of analysis used here. This study calculates crime concentrations at the macro-geographic level (police force jurisdiction), which contributes to the crime concentration seen. This is a common problem with geographic studies more generally; findings depend on the size of the area of study. For example, if one calculated the crime concentration for a neighborhood within a city, there would be more lower (or higher) crime concentrations, depending on the neighborhoods chosen. Weisburd's law of crime concentration is really only a law at the city or jurisdiction level. Even some of the 43 jurisdictions analyzed here include multiple towns with varying levels of population density and urbanity. For this study, jurisdictions could have been further divided into those individual towns, which may have presented more clear findings on the relationship between population density, street segment length and crime concentrations. Yet, there is a limitation to collecting social and physical indicators at micro level (e.g., income, demographic, culture, business activities information around street segments) to explain how social and physical attributes impact on crime at certain places. For future studies, smaller jurisdictions further break down to multiple towns with varying levels of urbanity with detail social and physical data can help to understand the variations of crime concentrations at micro-geographic levels.

A second and similar limitation mentioned by Weisburd is that the calculation of crime concentration may vary depending on the specific microgeographic unit of analysis examined. For instance, street segments—the unit of analysis used here—may show different levels of crime concentration compared with other units of analysis such as street addresses, clusters of street segments, or defined geographic buffers (Weisburd, 2015). Sherman et al. (1989) used addresses, not street segments, when discovering the now famous 50% of crime in 3% of street segments finding. However, if larger units are used, for example census block groups or half-mile grids, more crime might be concentrated in even fewer places (or vice versa). Again, this study uses street segments for the purposes of comparison with Weisburd (2015). However, the finding of variability across jurisdictions would still likely be discovered if other micro-geographic units were used.

Hipp and Kim have already raised yet another limitation that stems from the short-term study of crime concentration. The calculations of crime concentrations could be sensitive to both temporal fluctuations and the temporal unit of analysis used. This paper only examines 2016 crime patterns. A longitudinal study of crime concentrations over a long length of time would be needed to fully explore this limitation. For a longitudinal study, it is important to measure stability and variations of crime concentrations at macro-geographic levels (jurisdictions) across years to measure whether overall crime concentrations fall within a narrow bandwidth. For the analysis, generalized Gini coefficient is useful to compare level of crime concentrations over years. Also, measuring stability of crime concentration at micro-geographic levels (street segment) is necessary to explain whether criminological theories account for the variability of crime patterns at different street segments.

A major limitation of the study is with the data itself. Not having access to the raw police data itself, freely available online data from data.police.uk provided was used. However, in order to protect the privacy of victims, data.police.uk replaces certain crime coordinates with a master list of “snap points”. The master lists of “snap points” were created by the police.uk website developers according to the following rule: Any snap point, which had fewer than eight addresses associated with it were discarded to protect the privacy of victims (Tompson et al., 2015:102). As Tompson et al. (2015) note, “If the nearest snap point is over 20 km away, coordinates of zero are assigned so that the crime is not shown on the subsequent map” (p. 98). Thompson et al. (2015) argue that data.police.uk thus modifies its location data which underestimates crime locations. Unfortunately, compared to the U.S., this is the only publicly available dataset that can be used to examine *all* jurisdictions in a nation, and is therefore used here. In the future, perhaps all jurisdictions within a state in the U.S. might have data available for analysis so that a similar analysis can be conducted. However, even with this limitation, it is confident that even with the raw data that the variability in crime concentrations would be found.

Despite these limitations, this study adds to our understanding of whether a universal “law” of crime concentrations exists and proposes that human ecology is highly related to crime concentrations in specific jurisdictions. Given existing theoretical and empirical work, the likelihood of a law as proposed by Weisburd (2015) seems more likely when considered as an equation rather than a steadfast law. Because crime is “tightly coupled” to places, and criminological theories support the strong relationship between crime and place that a small number of micro places generate considerable amount of crime, this may explain why there are narrow bandwidths of crime concentration across places. Further research is needed about how specific crime types concentrate and how the routines activities of people, the environmental characteristics of places, and police and other prevention activity contribute to or mitigate crime concentrations. The findings of street segment length is likely indicative of activities and environments on short segments versus long as well as how cities were developed and planned. However, knowing which short segments are most susceptible to crime (and why) is the important question for further research.

In conclusion, this study confirms that Weisburd's law of crime concentration is generally supported. However, variations (and explanations of those variations) indicate that the law can be conceptualized as an equation, rather than a steadfast principle. Further, because it is a human law, the equation may be much more complicated than other laws in the physical sciences. Take for example Newton's law of gravity. While generally Newton's law states that gravitational force is 9.807 m/s^2, Newton's law does vary depending on the location, altitude and the density of the earth (which varies across specific locations). The law of crime concentration is not as specific, and potentially varies greatly depending on location. Given that human behavior is less easily measured, more differentiated, more complicated, geographically mobile, and less stable than the earth's density, the equation for the law of crime concentration becomes even more complex. Further, while the bandwidth of crime concentration could be considered generally "narrow", it also needs many more tests to see exactly how narrow the bandwidth is, and for what types of crimes one is considering. The law depends on the spatial and temporal units of analysis (as well as the quality of the data) being employed to calculate crime concentrations. Given this complexity and speculation, whether this equation should be considered a "law" or "principle" is up for debate.

APPENDIX:

Table A1. Crime Amount and Number of Street Segments for 43 Police Jurisdictions in England and Wales in 2016

Police Force	Total Crime	Violent Crime	Property Crime	Disorder and Drug Crime	Number of Street Segments
Avon and Somerset	130,752	36,243	58,148	36,361	87,501
Bedfordshire	62,330	11,623	26,174	24,533	24,260
Cambridgeshire	74,355	14,891	32,903	26,561	41,487
Cheshire	82,206	16,881	28,879	36,446	58,706
City of London	5,675	881	3,365	1,429	938
Cleveland	90,943	14,287	32,298	44,358	29,374
Cumbria	36,377	8,471	14,270	13,636	48,405
Derbyshire	92,304	14,429	34,250	43,625	49,282
Devon & Cornwall	116,327	27,411	39,735	49,181	135,573
Dorset	64,120	12,498	25,261	26,361	40,287
Durham	60,145	13,681	23,017	23,447	41,099
Dyfed-Powys	36,754	7,839	11,042	17,873	70,538
Essex	160,415	36,641	67,853	55,921	73,640
Gloucestershire	51,636	7,535	19,684	24,417	38,745
Greater Manchester	339,053	70,330	140,722	128,001	128,494
Gwent	58,208	11,599	24,250	22,359	35,744
Hampshire	169,633	31,769	67,431	70,433	94,003
Hertfordshire	96,355	19,105	40,185	37,065	47,590
Humberside	86,954	22,882	43,614	20,458	48,452
Kent	136,226	37,574	56,574	42,078	79,513
Lancashire	171,881	30,106	62,570	79,205	92,660
Leicestershire	79,780	16,450	42,525	20,805	44,074
Lincolnshire	88,220	15,026	32,337	40,857	47,606
Merseyside	151,800	30,998	59,571	61,231	59,074
Metropolitan	915,444	222,188	419,305	273,951	176,558
Norfolk	64,007	16,730	24,237	23,040	58,900
North Wales	56,735	14,478	21,208	21,049	61,889
North Yorkshire	64,066	10,967	22,295	30,804	35,903

Northamptonshire	85,468	18,113	34,391	32,964	84,269
Northumbria	166,631	35,854	65,997	64,780	65,715
Nottinghamshire	109,442	23,070	45,249	41,123	47,283
South Wales	119,811	31,448	51,296	37,067	66,078
South Yorkshire	177,756	26,801	65,592	85,363	58,326
Staffordshire	92,535	24,514	31,126	36,895	58,782
Suffolk	53,046	14,451	22,921	15,674	45,279
Surrey	59,395	14,510	24,842	20,043	54,832
Sussex	128,795	32,956	51,136	44,703	75,970
Thames Valley	153,797	33,424	81,102	39,271	110,785
Warwickshire	45,531	10,459	18,423	16,649	31,116
West Mercia	105,298	25,676	36,831	42,791	87,890
West Midlands	247,713	58,191	122,953	66,569	86,820
West Yorkshire	270,753	65,579	126,576	78,598	110,071
Wiltshire	53,674	14,079	21,603	17,992	40,709
England & Wales	**5,412,345**	**1,202,638**	**2,273,741**	**1,935,967**	**2,774,220**
Average	125,501	27,968	52,878	45,022	64,517

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BIOGRAPHY

Sangjun Park received Bachelor of Arts from Michigan State University in 2009. He received Master of Arts from University of Cincinnati in 2013. He was employed as a graduate research at Community Design Center, University of Cincinnati for 2 years. He had worked for 5 years at the Center for Evidence-Based Crime Policy during his Ph.D. program.