The Nexus between Contexts of Crime Risk and Socioeconomic Inequality on the Rates of Violent Crime Victimization: Evidence from Variations across Neighborhoods in Bogotá, Chicago, and Paris

by

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ABSTRACT

The Nexus Between Contexts of Crime Risk and Socioeconomic Inequality on the Rate of Violent Crime Victimization: Evidence from Variations across Neighborhoods in Bogotá, Chicago, and Paris

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Purpose: This study presents a novel approach to the study of neighborhood effects on crime. In this sense, it tests the varying influences that unique contexts of crime risk and socioeconomic inequality present on the spatial distribution of violent crime victimization rates across neighborhoods in the cities of Bogotá, Chicago, and Paris.

Methods: This analysis utilizes both micro and neighborhood-level social and physical variables to study the spatial association between unique contexts of relative deprivation and crime risk with an increase in neighborhood-level violent crime rates. The presence of risky environments across neighborhoods is measured with ANROC and calculated using the RTM technique. The second independent variable is based on neighborhood-level Gini index data for income inequality. The association between the two predictors is tested using different multivariate OLS regression models.

Results: As per the results of this research, unique contexts of socioeconomic inequality and environmental risk are positively associated with an increase in neighborhood-level rates of violent crime victimization. This spatial relationship holds across the three case studies presented in this study with varying degrees of association regarding the inequality measure in three case studies.

Conclusions: The current study proposes combining the study of community-specific contexts of crime risk and social contexts of socioeconomic inequality to explain the spatial distribution of violent crime rates across neighborhoods in a variety of study settings. The policy implications of this research study support the need for scientific evidence in the development of community-based strategies to improve risk management efforts to prevent and reduce violent crime. Additionally, community outreach programs and other social initiatives should be established to reduce the pervasive effect created by unique social contexts of socioeconomic inequality across neighborhoods.

Keywords: *Crime risk, Inequality, Neighborhood Effects, Risk Terrain Modeling, Ecology, Social Processes, Residential Segregation*

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CHAPTER 1. INTRODUCTION

"We must work together to ensure the equitable distribution of wealth, opportunity, and power in our society."

- Nelson Mandela

Socioeconomic inequality is not a modern concept linked to our time but is rather a reality that throughout history has affected the most basic principles of democracy and the rule of law (Eckstein & Wickham-Crowley, 2003). It is a phenomenon that is not only inevitable but also common in today's modern market economies, bolstering undesirable effects, such as violence and crime. Inequality figures vary not only from one city to another but also from one neighborhood to another. Such variations have a direct impact on entire communities affected by structural inequality, which plays a determinant role at explaining the variations of crime rates across entire neighborhoods (Ousey & Lee, 2013). As noted by Agnew (1999), the use of neighborhood-level indicators can reduce the chances of data spuriousness commonly found when using aggregate data. Also, disaggregated neighborhood-level data can reduce the chances of other data problems as a result of a process known as the "ecological fallacy" (Sampson and Wilson, 1995).

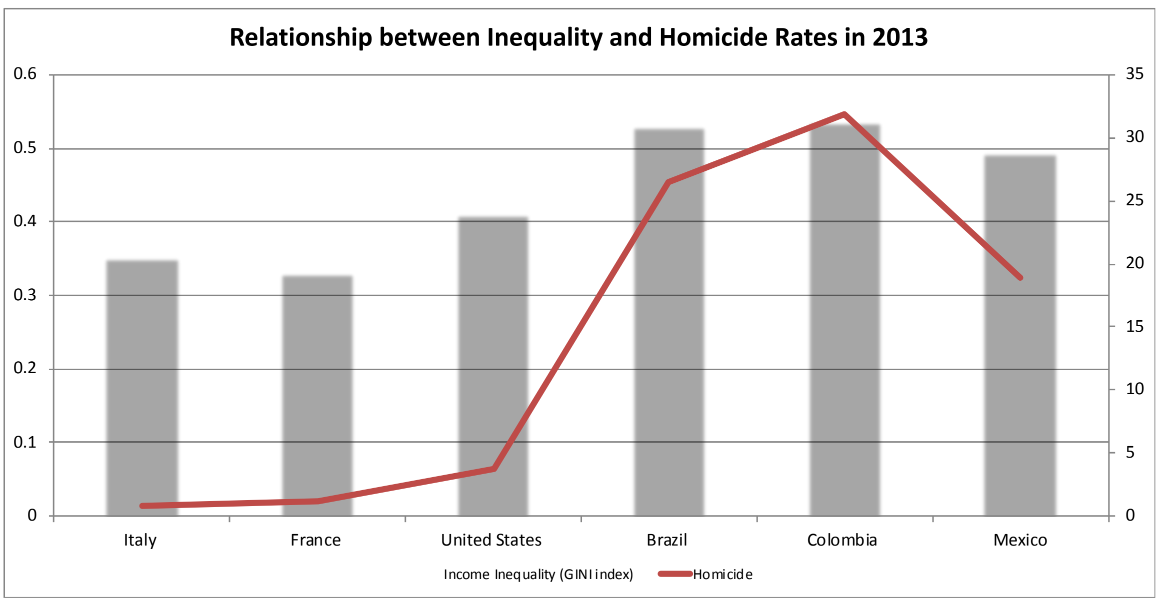
As suggested by the existing economic literature on crime (Fajnzylber et al., 2002; Kelly, 2000; Blau & Blau, 1982; Roberts & Willits, 2014; Demombynes & Ozler, 2005; Enamorado et al., 2014; Hooghe et al., 2010; Hipp, 2007; Krahn et al., 1986; Neapolitan, 1994; Ousey & Lee, 2013), contexts of inequality are associated with an increase in violent crime rates. Still, most research efforts have failed to include a measure for crime risk when assessing the overall effect of inequality on crime. It is therefore important to analyze the underlying conditions under which the unequal distribution of economic resources within communities may impact violent outcomes. More precisely, how contexts of socioeconomic inequality have an influence on individual-level motivations leading to expressions of criminal behavior across neighborhood environments.

From an environmental standpoint, physical contexts are known to have a strong influence in explaining why crime occurs at some locations and not others (Caplan, 2011). In this regard, the theory of risky places suggests that risk is a function of *threat*, *vulnerability*, and *consequence* (Kennedy & Caplan, 2012). As indicated by Kennedy et al. (2015): "evidence suggests that analyzing the risk heterogeneity of a landscape along with event-dependent assessments of crime is useful for generating a more complete understanding of crime problems at specific places" (p. 2). Also, it is widely known that crime incidents are not equally distributed in time or space (Wortley & Mozerolle, 2013). Instead, these tend to cluster around particular areas, known as criminal hotspots. As Wortley and Mozerolle (2013) suggest, it is through the combination of situational forces that enable potential offenders to commit a crime, also known as precipitators, and the rational assessment of the existing criminal opportunities that act as facilitators in the occurrence of a criminal event. As a result, a potential offender is more likely to commit a crime when a series of locational precipitators and opportunities exist. Thus, and based on the theoretical framework on crime and space, this study hypothesizes that violent crime incidents tend to be more frequent in neighborhoods where unique contexts of crime risk and socio-economic inequality are in display.

For instance, Latin America, the world region with the highest levels of socioeconomic inequality (Eckstein et al., 2003; Lopez-Calva et al., 2015), stands as the world region with the highest rates of violent-crime victimization (UNODC, 2013). Not surprisingly, this region is known for its continued civil conflicts, as well as by its elevated levels of crime and social instability (Stiglitz, 2012). According to Wilkinson and Pickett's (2010) research findings, unequal societies are more prone to suffer from higher crime rates and social dysfunction. Similarly, The Organization for Economic Cooperation and Development (OECD) (2015) reported that, over the last decade, the level of inequality has continued to increase in many parts of the world. A process sustained by the increased gap between the rich and the poor. A Global phenomenon that affects not only developing countries but also industrialized economies, which are suffering from a failing middle class (Stiglitz, 2012). In fact, inequality in Europe and the United States is higher today than it was in the 1980s (European Commission, 2010). This common trend among industrialized economies is indicative of the state of continual change that is shaping the labor market, linked to globalization and technological change. As noted by Stiglitz (2012), in the near future and if no major changes occur, more inequality and fewer opportunities are expected to occur. It is therefore fundamental to study the spillover effects that growing levels of inequality produce across urban environments in different parts of the world.

To better understand the macro-societal association between higher levels of inequality and violent crime, a preliminary comparison was made at the country level. As seen in Figure 1, the relationship between income inequality (Gini index) and intentional homicide rates presents a pattern among this subset of six countries across different world regions. First, European nations like France or Italy show reduced levels of income inequality and homicide victimization rates. Meanwhile, the United States displays moderate levels of inequality and homicide victimization. Lastly, Latin American nations like Brazil, Colombia, and Mexico all present high levels of income inequality and exceptionally high levels of homicide victimization. This macro perspective allowed to identify three potential countries, one for each of these subgroups, to study how variations in neighborhood-level inequality correlate with the distribution of violent crime victimization rates. Having this objective in mind and given the availability of data from these geographies, the current study analyzed neighborhood effects on violent crimes across the cities of Bogotá (Colombia's capital and largest city), Chicago (The United States' third largest city), and Paris (France's capital and largest city).

Figure 1.The relationship between inequality and homicide rates



Source: World Bank and UNODC

With this objective in mind, the current study analyzes how unique physical and social contexts interact to create neighborhood environments that are conducive to displays or expressions of deviant behaviors. By analyzing neighborhoods in cities from largely different world regions, this study also accounted for societal, institutional, and regional variations between these city environments. These regional variations are expected to translate into differences in the overall effect that these contexts produce across geographies.

To analyze this phenomenon, this study hypothesizes that unique neighborhood contexts of crime risk and socioeconomic inequality are associated with an increase in violent crime victimization rates. Additionally, the current study tested separately the spatial influences that unique contexts of crime risk and socioeconomic inequality present on the spatial distribution of violent crime victimization rates across neighborhoods. It is expected that the results from this multijurisdictional neighborhood-level analysis will validate the main hypothesis of this study, given that unique contexts of crime risk and socioeconomic inequality are associated with increased victimization rates across case studies.

In order to better understand variations at the neighborhood level, it is important to understand globally the regional and national contexts surrounding these cities. According to UN-HABITAT (2012), economic development tends to go hand in hand with a more equitable income distribution, which isn't the case in Latin America where inequalities are stark. As previously noted, Latin America is today the world's most unequal region (World Economic Forum, 2016), thus making this region an ideal study setting to test the relationship between contexts of inequality and violent crime activity. In this regard, the city of Bogotá presents a unique opportunity for this study, given its geographic location in the Latin American regional context and its rich repository of geographical information systems (GIS) data. Moreover, the city of Bogotá offers stratification data on its urban spaces based on a series of social and ecological features, thus allowing to control for perceived class distribution throughout the city and across its neighborhoods. This type of micro-level data is unique to Colombia with numerous studies (see Uribe-Mallarino, 2008; Thibert & Osorio, 2014; Giménez-Santana et al., 2018) linking varying strata levels to the distribution of socioeconomic status (SES) across community-environments.

The next set of geographies, namely Chicago and Paris, belong to a regional group of industrialized OECD countries, both of which have several institutional and economic differences. As Peter Hall and David Soskice (2001) suggested in their study of varieties of capitalism, there is a divide between liberal and coordinated economies that can explain institutional variations between nations. On the one hand, mixed market economies like France are characterized by their publicly funded welfare systems that provide a "financial cushion" for the jobless and other benefits like sick pay insurance or parental leave coverage to its citizens, while incorporating the market mechanisms typical of liberal economies. On the other hand, liberal market economies like in the United States have a lower degree of collective bargaining and access to welfare programs and are more reliant on market forces to coordinate economic activities (e.g., deregulated job market).

The institutional variations between these two groups have important implications to understand the determinants that contexts of socioeconomic inequality present within their urban settings. In comparative terms, the United States stands as the developed country with the highest level of inequality in the OECD club of countries, while France has experienced a decrease in inequality figures since the 1980s (Rueda & Pontusson, 2000). The differences arising between these two developed economies offer a unique opportunity to better understand the variations of inequality and its effect on violent crime within two distinctive settings. As such, this sub-group of geographies became highly relevant to this study to better understand the dynamics of varying contexts of criminal risk and socioeconomic inequality on neighborhood-level violent crime rates.

According to the World Bank's LAC Equity Lab, over the last decade, there has been a continual decline in poverty rates across Latin America and the Caribbean. However, inequality has remained constant throughout the region with a Gini coefficient of 0.52, suggesting a vast income gap (World Bank, 2013). Based on Stiglitz's (2012) research findings, a Gini coefficient over 0.5 indicates an elevated level of inequality. The Gini indicator for inequality is commonly studied at the national and city levels, thus failing to account for variations at the community level. Studying inequality across neighborhoods, and not just across cities or nations, offers this study the opportunity to identify unique patterns in the distribution of inequality across urban contexts that would otherwise be difficult to interpret using higher levels of aggregation. For example, a number of neighborhoods in Paris present very high levels of inequality with a Gini coefficient of 0.68, a significantly higher level of inequality compared to France's or Paris's average indicator (INSEE, 2012). This is indicative of the dangers of using aggregate data to infer certain causal relationships as the risk of data spuriousness or "ecological fallacy" (Sampson & Wilson, 1995) increases when analyzing large jurisdictions.

As seen in Table 1, in the city of Bogotá, the Gini index for 2011 was estimated at 0.54 at the municipal level (Cediel Sanchez & Sanchez Guerrero, 2016), a value that closely resembles Colombia's national inequality level with a Gini coefficient of 0.55 over the same period of time. As noted before, this level of inequality is commonly considered elevated (see Stiglitz, 2012). However, the level of inequality across Bogotá's localities[1] is significantly different than that of the previous two metrics. For instance, inequality oscillates between 0.37, considered low, to 0.59, higher than the city's average level. Similarly, France's national statistical office (Institut National de la Statistique et des Études Économiques – INSEE, 2012) estimated that Paris had a Gini coefficient of 0.5 in the year 2011, which contrasts with the country's overall inequality index of just 0.33. However, by taking a closer look at Paris' neighborhoods[2], the range of inequality varies from a low Gini coefficient of 0.27 to a high of 0.68, considered a high level of inequality.

Lastly, in the city of Chicago, the estimated level of inequality, as measured by the Gini index, was 0.53 for the calendar year 2012, which was slightly over the U.S. national inequality rate of 0.48 over the same period. Once again, neighborhood-level figures offer a contrasting perspective across Chicago's neighborhoods[3], where some communities present a very low level of inequality with a Gini index of just 0.25 compared to the extremely high levels of inequality in neighborhoods with a Gini coefficient of 0.72. Therefore, it is important to note that the scale at which inequality is observed alters the reality that people live in their immediate environment, their communities, and their neighborhoods.

As shown in Table 1, large differences between these metrics indicate a high level of variation between neighborhoods across the three cities. However, it is also important

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[1] The city of Bogotá is administratively divided in 19 localities and 111 statistical subdivisions or UPZs (an acronym for "zonal building units"). The current study operationalized UPZ units as Bogotá's neighborhood units of analysis.
[2] The city of Paris is divided in a total of 830 IRIS units (an acronym for "aggregated units for statistical information") and administratively subdivided in 20 "arrondissements". The current study operationalized IRIS units as Paris' neighborhood units of analysis.
[3] The city of Chicago is divided for statistical purposes in 797 census-tracts. The current study operationalized census-tract units as Chicago's neighborhood units of analysis.

to note that large cities are more prone to display higher levels of inequality than smaller cities (Long et al., 1977; Nord, 1980). Moreover, previous studies have demonstrated that large MSAs (metropolitan statistical areas) with a higher population tend to display higher levels of socioeconomic inequality (Long et al., 1977). For the purpose of this study, only large cities were analyzed to observe the relationship between varying levels of inequality and crime risk on violent crime victimization rates. Future research studies should analyze smaller cities to test the relationship between contexts of inequality and crime.

Table 1. Inequality and violent crime statistics during calendar year 2012

	Inequality[4] (Gini index)		**Violent Crime** (Rate per 1,000 population)
City / Indicator	**Municipal level**	**Neighborhood-level**[5]	**Neighborhood-level**[6]
Bogotá, Colombia	0.54	0.37 – 0.59[7]	0 – 54
Chicago, United States	0.53	0.25 – 0.72	0 – 51
Paris, France	0.5	0.27 – 0.68	0 – 11

Sources: DANE-Bogotá 2011, INSEE 2012, U.S. Census Bureau 2012, Colombia's National Police, Prefecture of Police in Paris (DSPAP), and Chicago's Police Department.

[4] Inequality data displayed for the cities of Bogotá and Paris is for calendar year 2011, as no data was available for the year 2012.
[5] Neighborhood-level Gini index (Minimum and Maximum values displayed).
[6] Neighborhood-level violent crime rates per 1,000 people (Minimum and Maximum values displayed).
[7] Bogotá's statistical agency only offers inequality data disaggregated at the locality-level within the city of Bogotá. Each one of the 19 localities are composed of a varying number of UPZs, the city's standard statistical subdivision. To overcome this limitation and be able to control for variations across Bogotá's neighborhoods, the Gini index assigned to each locality was incorporated to the different UPZs composing these larger geographical subdivisions. Thus, the Gini index assigned to Bogotá's subdivisions, or UPZs, should be taken with caution as these values represent an approximate value of the existing level of inequality within each locality.

Major differences exist in violent crime victimization rates across different neighborhoods in each of the three geographies in this study, with Chicago accounting for more than five times the amount of violent crimes taking place in Paris. There is a significant variation in victimization across neighborhoods, with violent crime rates fluctuating from no events to more than 52 crimes per 1,000 people in some neighborhoods. Most importantly, all three cases presented major differences in their levels of violent crime victimization while displaying similar levels of inequality. Thus, it is important to analyze the relationship between contexts of crime risk and varying levels of socioeconomic inequality to explain the presence, or absence, of violent crime incidents across these regionally differentiated case studies. Also, it is important to address the institutional, regional, and contextual differences driving criminal outcomes across neighborhoods in these three cities.

As a result, this study proposes a cross-neighborhood comparison of three urban settings located in largely distinctive world regions, namely, Europe, North America, and Latin America. As with other studies, regional differences tend to offer unique challenges when testing for similar sets of variables across different global jurisdictions. As noted by Solt (2009), “research on inequality’s causes and consequences has been greatly hampered by data issues, namely, the limited number and often questionable comparability of the observations available for quantitate cross-national analysis” (p. 1). To prevent this and other issues arising from data comparisons across different cities in different countries, this study used a standardized unit of measurement for inequality, the Gini index, which allowed to overcome the aforementioned limitation. Moreover, and through the use of empirical micro and neighborhood-level data, the relationship between criminal risk and inequality was tested and its relationship estimated over the existing rates of violent crime victimization for each neighborhood within the cities of Bogotá, Chicago, and Paris.

The current study was structured around seven thematic chapters. The first chapter presented a set of introductory remarks and offered an overview of this study's research hypotheses. The second chapter revisited the extant literature on inequality and violent crime victimization, and Chapter 3 focused on reviewing the literature on crime analysis, social disorganization and environmental criminology theories. Then, Chapter 4 presented the current study's hypotheses and research methods, including a step-by-step description on the use of the risk terrain modeling (RTM) technique, and the procedures for creating ANROC measures to identify risky neighborhood environments. Chapters 5 to 7 separately addressed the main research question of this study by analyzing the relationship between unique contexts of the crime risk and socioeconomic inequality across neighborhoods in Paris, Bogotá, and Chicago. Lastly, Chapter 8 offered a comparative analysis of this study's results across its three case studies, discussed the main policy implications, proposed future avenues for research, and established the conclusions for this analysis.

CHAPTER 2: INEQUALITY AND VIOLENT CRIME REVISITED

"There are crimes of passion and crimes of logic. The boundary between them is not clearly defined."

- Albert Camus

To date, a wide range of studies have addressed the relationship between unique contexts of inequality and violent crime victimization rates. As inequality has grown to become an extended concern throughout the world, so has the interest shown by researchers to study the consequences that these changes entail. In a recent publication, Stiglitz (2012) noted that "The experience of Latin America, the region of the world with the highest level of inequality, foreshadows what lies ahead. Many of these countries were mired in civil conflict for decades and suffered high levels of criminality and social instability. Social cohesion simply did not exist" (p. 105). Thus, Stiglitz emphasized the damaging effect that sustained inequality has on social values and norms. A societal process that leads to an increase in violence and social disorganization as a result of deprivation and strain.

Several theories have already dealt with the pervasive effects of inequality. For example, researchers have explored the relative deprivation theory or strain theory (Agnew, 1999; Fajnzylber et al., 2002; Hipp, 2007; Jacobs, 1981; Merton, 1938), which refers to the process by which individuals living in communities with high levels of inequality are affected by strain or frustration. Agnew (1999) suggested that, according to the relative deprivation theory, community characteristics influence "whether individuals compare themselves to advantaged others, decide that they want and deserve what these others have, and decide that they cannot get what these others have through legitimate channels" (p 125). In other words, deviant behaviors are likely to emerge within contexts of relative deprivation as individuals use illegitimate means to obtain personal gains.

Another dominant explanation derives from the social disorganization theory, which was initially developed in the early 1930s by the Chicago school theorists Clifford Shaw and Henry McKay. That theory suggests that poverty and inequality are directly responsible for weakening social controls, leading, as a result, to an increase in violence and crime. That theoretical framework has been consistently extended over the last years with some major contributions to the literature (Bursik, 1988; Sampson, 1985; Sampson & Groves, 1989; Sampson & Wilson, 1985). Sampson (1985, 2012) suggested revisiting Shaw and McKay's social disorganization theory and proposed instead a theory of collective efficacy to better understand today's neighborhood social dynamics. In this sense, Sampson suggested that communities nowadays present a lower influence deriving from a lack of personal ties between neighbors and that other social mechanisms are sufficient to create community efficacy. Other theories, such as the social distance theory (Blau, 1977), the group threat theory (Quillian, 1995), the deviance theory (Stark, 1987), or the consolidated inequality theory (Blau & Blau, 1982) have as well contributed to the extant literature supporting the relationship between inequality and violent crime victimization.

Ecological theories

Chicago School theorists Shaw and McKay (1942) proposed the social disorganization theory, a fundamental theoretical framework that underscores the importance of crime correlates at the neighborhood level. This model suggests the effects of three key structural factors – low economic status, ethnic heterogeneity and residential mobility – that weaken social controls and, thus, lead to higher delinquency rates (Shaw & McKay, 1942). According to this theory, crime rate increases are fueled by rapid social changes that weaken the underlying mechanisms of social control, making personal relations more impersonal and anonymous. Sampson and Wilson (1995, p. 178) noted that "residential inequality gives rise to the social isolation and ecological concentration of the truly disadvantaged, which in turn leads to structural barriers and cultural adaptations that undermine social organization and hence the control of crime." Thus, socioeconomic inequality is linked to a series of social processes that ultimately lead to social disorganization and crime.

One of the main dimensions described by the social disorganization theory is how a lack of social cohesion can increase the likelihood of violence and crime. In the low-income areas, where there is a higher level of deprivation and frustration, the probability of victimization dramatically increases because of a notorious lack of opportunities. As described by Shaw and McKay (1942), "Crime may be regarded as one of the means employed by people to acquire, or to attempt to acquire, the economic and social values generally idealized in our culture, which persons in other circumstances acquire by conventional means" (p. 439). As a result, some people may find it rewarding to improve their social and economic status through criminal activity.

In these environments, the use of "unconventional ways" to secure material goods becomes embedded in the urban culture of the disadvantaged, who lack the necessary opportunities to acquire these values by conventional means. Shaw and Mckay (1942) addressed the effects of inequality and poverty on crime, mostly among the juvenile population, when stating the following:

> *"Among children and young people residing in low-income areas, interests in acquiring material goods and enhancing personal status are developed which are often difficult to realize by legitimate means because of limited access to the necessary facilities and opportunities"* (p. 318).

In these contexts of relative deprivation, young adults and other individuals resort to illegitimate means to secure access to resources they feel deprived from obtaining through other means. The work of Shaw and Mckay (1942) challenged the existing theories focused on the role of "individuals" to explain crime by a theory of "places" that are conducive to criminal activity (Kubrin & Weitzer, 2003). According to Sampson (1985), neighborhood characteristics like poverty, inequality, mobility or structural density have gained ground in criminological research for their capacity to predict the risk of victimization independently of individual-level characteristics, thus, the importance of identifying the social factors that are conducive to higher levels of violent crime victimization.

Strain theories

The general strain theory, or GST, supports the notion that strain is a major source of criminal motivation and that a series of community-specific characteristics can explain variations in crime rates. For instance, neighborhoods suffering from economic deprivation and inequality that are overcrowded or present high mobility will all present community-specific characteristics leading to strain (Agnew, 1999). In particular, the relative deprivation theory refers to the feeling of dispossession and dissatisfaction towards society and social order that can make individuals more prone to use illegitimate means, such as violence and crime, against both the rich and the poor (Kelly, 2000). According to Fajnzylber et al. (2002), "Inequality breeds social tensions as the less well-off feel dispossessed when compared with wealthier individuals" (p. 2). The persistence of structural inequality can undermine core societal values, thus making the disadvantaged develop feelings of alienation, resentment, and hostility (Ousey & Lee, 2013). However, deprivation may occur at any level of the income distribution curve. In fact, the wealthy may also feel "deprived" when compared to other individuals and feel motivated to engage in criminal behavior, a social characteristic attributed to those in poverty (Ousey & Lee, 2013).

According to Hipp (2007, p. 5): "individuals compare themselves with others in their reference group and respond with deviant behavior if they feel that they have an inequitable economic share." Arguably, it could be interpreted that individuals living in the same community, or within proximity, may constitute one of these so-called "reference groups" because of their geographic proximity but also their close interaction with one another. This theory supports the argument that inequality is a major source of criminal motivation, whereas the absolute deprivation theory links such motivation to poverty. This distinction is made to separately control for the effects of these two specific social contexts and their effects on crime, which are analyzed later in this chapter.

Macro-social theories

Social distance theory posits that individuals living in unequal communities are more likely to have fewer intergroup relations, thus impacting neighborhood crime levels (Blau, 1977; Hipp, 2007). For instance, Blau proposes a distinction between inequalities within and across communities, by noting that while inequalities within communities reduce social associations, they do not "inhibit them as much as do inequalities that are reinforced by residential segregation among strata" (Blau, 1977, p. 47). In other words, inequality can be reinforced by the segregation of groups concentrating resources in different neighborhoods. This theory is closely connected to the social disorganization theory, which posits out that social distance or reduced relations between neighbors can undermine social controls leading to an increase in crime rates (Hipp, 2007). In a recent study, Kang (2015) found that the correlation between within-neighborhood inequality and crime was weak or negative. Therefore, the impact of within-neighborhood inequality is expected to be limited when compared to across neighborhood contexts of inequality reinforced by residential segregation. The current study only addressed the latter by testing how varying contexts of inequality impact the spatial distribution of victimization rates.

Similarly, the consolidated inequality theory (Blau & Blau, 1982) postulates that socioeconomic inequalities are associated with ascribed positions, a factor that consolidates and reinforces racial and class differences leading to social conflict. Thus, according to this theory, ascribed inequalities are responsible for undermining social integration at the community level through multiple parallel social differences that separate and widens the divide between ethnic groups and social classes, leading as a result to prevalent animosities. A social reality addressed by Blau and Blau (1982) when they state that:

> *"Ascriptive socioeconomic inequalities undermine the social integration of a community by creating multiple parallel social differences which widen the separations between ethnic groups and between social classes, and it creates a situation characterized by much social disorganization and prevalent latent animosities."* (p. 119).

It is therefore the lack of opportunities perceived by the poor who seek to attain the status of the rich that produces a state of social disorganization and disorientation within local social groups. This prevailing context of disorganization and anomie should increase conflict, as individuals feel the antagonistic urge to release tension, which results in an increase in violent crime (Blau & Blau, 1982).

At this point, it is important to consider the differences arising between inequality and poverty, or the distinction between relative and absolute deprivation. Inequality results from a major concentration of wealth in the hands of a few, where some have thousands of dollars on which to live, and others have millions of dollars. The European Commission (2010) defines inequality as: “The disparities in a distribution of monetary resources between or within populations.” Alternatively, Blau (1977) refers to the criterion of degree of inequality as: “The average difference in status between any two pairs relative to average status” (p. 31). In both cases, the core argument that defines inequality is linked to the existence of large differences in status, class, and access to resources within individuals in a given society.

The most widely used empirical measure to quantify inequality is the Gini index (Blau, 1977). This coefficient is calculated by a Lorenz curve of income distribution that measures the possible deviation from a line of perfect equality (see World Bank, 2010). Under this measurement, an index of 0 represents perfect equality while an index of 1 is equal to perfect inequality. Gini is calculated as a ratio of the areas on the Lorenz curve diagram, where A is the area between the line of perfect equality and the Lorenz curve, and B is the area under the Lorenz curve.

Thus, the resulting equation to calculate the Gini coefficient is:

$$\text{Gini Coefficient (G)} = \frac{A}{A+B}$$

However, the unequal distribution of income does not necessarily imply that there is poverty, and poverty does not necessarily imply that there is inequality. According to the World Bank's definition, a person is considered to be poor "if his or her consumption or income level falls below some minimum level necessary to meet basic needs" (World Bank, 2013). The lack of a standardized measure for poverty has lead scholars studying the poverty-homicide relationship to use a series of proxies such as infant mortality to measure inequality. The current study did not include a measure for poverty within its analyses; however, future studies should consider comparing the effects of inequality and poverty on the distribution of violent crime activity.

A review of the economic literature on crime

As stated earlier, prior studies have found empirical evidence on the nexus between crime and inequality (see Blau & Blau, 1982; Kelly, 2000; Fajnzylber et al., 2002; Soares, 2002; Hipp, 2007; Choe, 2008; Ousey & Lee, 2013; Enamorado et al., 2014). These findings give support to the relative deprivation explanation, given that crime in areas with high income inequality tend to be greater when compared to other areas because of an array of economic, social, and ecological factors. The current study's focus was to test how unique contexts of socioeconomic inequality and crime risk can explain the spatial distribution of violent crime victimization rates across neighborhoods in three large global cities.

In a recent study, Hipp (2007) found a positive association between income inequality measured at the census tract level and various crime types across nineteen cities in the United States. According to Hipp's (2007) research findings, "Not only is the composition of race and class in neighborhoods important for explaining crime rates, but also that the distribution of race and class within neighborhoods has important effects" (p. 28). Similarly, Blau and Blau (1982) found a positive association between inequality and violent crime victimization in a study comparing America's largest 125 standard metropolitan statistical areas (SMSAs). These findings not only support the argument that relative deprivation is a major source of criminal motivation but also that when controlling for inequality, the positive relationship between poverty and violent crime disappears (Blau & Blau, 1982). In other words, Blau and Blau's study suggests that inequality is a better predictor than poverty at explaining criminal violence and that a decrease in the degree of inequality could lead to a reduction in the offense rates, as the most disadvantaged feel empowered enough to abandon criminal activities through access to new opportunities.

Previous research studies analyzing the various effects of inequality on crime have focused either at the national level (Allen, 1996; Roberts & Willits, 2014; Choe, 2008; Demombynes & Ozler, 2005; Hooghe et al., 2010), cross-national level (Fajnzylber et al, 2002; Bourguignon, 1998; Krahn et al., 1986; Messner, 1980; Neapolitan, 1994; Pridemore, 2011), or the community-level (Blau & Blau, 1982; Hipp, 2007; Kelly, 2000; Kang, 2015; Messner, 1982; Sampson, 1985; Williams, 1984). It is nonetheless important to note that a number of these neighborhood-level analyses were commonly conducted using SMSAs as their unit for these studies (see Blau & Blau, 1982; Williams, 1984;

Messner 1982). These units present higher levels of aggregation with populations of at least 50,000 people per SMSA, while instance census tracts are limited to a population size between 1,200 and 8,000 people[8].

According to Patterson (1991, p. 761), "smaller units of aggregation may provide a more meaningful frame of reference for many concepts in macro theories of criminal activity." Therefore, offering a better analysis framework that allows to understand the effect that macro-social variables have on crime outcomes. Moreover, individual's behavior is most likely to be impacted by social contexts to which the individual is most often exposed (Patterson, 1991). The current analysis resorted to use the smallest units of analysis[9] that were available, at the time of this analysis, to better understand the effect that varying context of inequality has on the distribution of crime outcomes.

Krahn et al. (1986) found a moderately sized positive relationship between inequality and homicide rates. Fajnzylber (2002) suggested that inequality, as measured by the Gini index, has a significant and positive effect on crime rates. A recent publication by Enamorado et al. (2014) found that an increase of 1% in the Gini coefficient for inequality increased the number of drug-related homicides in Mexico between 2007 and 2010 by as much as 36%. Choe (2008) found that relative income inequality at the state level, as measured by Gini, has a strong and robust impact on burglary and robbery incidents. According to Demombynes and Ozler's (2005) results, high inequality at the neighborhood level is associated with higher rates of both violent and property crimes. Poveda (2011)

[8] U.S. Census Bureau (https://www.census.gov/geo/reference/gtc/gtc_ct.html)

[9] The current study used the smallest units of analysis offering inequality data at their level of aggregation. For instance, in the United States block-level and census-group data offer a smaller unit of analysis than census-tract data but Gini data wasn't available at the block-level unit of analysis at the time this study was conducted.

suggested that inequality and crime were positively associated in a multi-city analysis in Colombia. Also, Kang (2015) found that across-neighborhood inequality is positively associated with an increase in crime by using census tract data from the 200 largest counties in the United States. These studies support the positive association between contexts of socioeconomic inequality and violent crime victimization rates.

Other studies rejected the association between these two measures. Chintrakarn and Herzer (2012) noted that an increase in income inequality leads to a decrease in crime as the demand for protection increases, thus reducing crime outcomes. Similarly, Pridemore (2011) determined that there is no association between inequality and homicide in most cases when controlling for poverty. In a study using NCS national household data, Sampson (1985) found no empirical support to the claim that income inequality is a major determinant to variations on neighborhood crime rates, and instead refers to other forms of inequality based on racial or ethnic differentiations. Lastly, to Allen (1996), inequality and social structure have no impact on property crime activity, while a reduction in inflation can reduce crime.

A number of studies have tested the relationship between inequality and crime at larger units of analysis, like the county level, city level, or even the country level. As noted before, the study of inequality and crime using large units of analysis can hinder important neighborhood-level variations that can increase the likelihood of obtaining misleading results. At the subnational level it is particularly relevant to the work of Kelly (2000), who used a large sample comprising all U.S. counties to analyze the relationship between crime and inequality. Kelly concluded by stating that the “most disadvantaged members of society face greater pressure and incentives to commit a crime in areas of high inequality”

(p. 537). This argument was opposed by Bourguignon, Núñez, and Sánchez (2003) who analyzed seven large Colombian cities, including Bogotá, over a twenty-year period but only found insignificant results on the link between income inequality and overall crime.

Other studies (see Messner, 1980; Nadanovsky & Cunha-Cruz, 2009; Bourguignon, 1998) opted to analyze the relationship between inequality and crime at the cross-national level. Messner (1980) used a sample of 39 countries to test the relationship between income inequality and other societal variables on national level murder rates. Based on Messner's findings, the income inequality measure explained 35% of the total variation in murder rates across the sample. Similarly, Nadanovsky and Cunha-Cruz (2009) found that low levels of income inequality and low impunity were related to a decrease in homicide rates in a cross-sectional ecological study between OECD nations, South, and Central American countries. These findings validate the positive association between contexts of inequality and homicide rates at the country-level.

Conclusion

The current chapter has presented a review of the extant literature on the relationship between contexts of inequality and crime. As noted, previous studies have addressed this question using very different units of analysis, ranging from cross-national studies to neighborhood-level analyses. The results obtained through these works differ with some authors rejecting the relationship between inequality and crime (Chintrakarn & Herzer, 2012; Pridemore, 2011; Sampson, 1985; Allen, 1996) while other scholars claim the opposite and find a significant association between these two measures (Blau & Blau, 1982; Kelly, 2000; Fajnzylber et al., 2002; Soares, 2002; Hipp, 2007; Choe, 2008; Ousey & Lee, 2013; Enamorado et al., 2014).

In most cases, neighborhood level comparative studies have remained insulated to the study of country-specific variations across geographies (see Hipp, 2007; Enamorado et al., 2014; Poveda, 2011), thus failing to account for variations across national and regional contexts. To close this theoretical gap, the current study used neighborhood-level data as its unit of analysis to compare variations across communities in three large cities from different world regions. The study of neighborhood effects in the cities of Bogotá, Chicago, and Paris, allowed not only to test the relationship between unique contexts of inequality and criminal risk on the distribution of violent crime rates, but also to account for broader societal and regional differences across these environments.

CHAPTER 3: IDENTIFYING CONTEXTS OF CRIMINAL RISK AT THE NEIGHBORHOOD LEVEL

> *"Everything is related to everything else, but near things are more related than distant things."*
>
> \- Waldo Tobler

Nowadays, access to large criminal databases, in conjunction with sophisticated geographic information system (GIS) technology, allows crime analysts to use an array of new analytical tools. This technological revolution has led to an unprecedented increase in the number of studies using spatial analysis, as well as, new innovative applications. In fact, different mapping techniques (e.g., hot spot analysis) have become integrated in the day-to-day operations of police departments across the United States and, increasingly, throughout the world. Yet police responses to crime continue to be inherently offender-focused instead of place-based (Caplan & Kennedy, 2016). It is therefore important to continue advancing in the search of new approaches that identify what contexts are conducive to a higher risk of victimization across geographies. Thus, enabling police departments and other security stakeholders to shift their current focus on offenders to responses that account for the effect that contexts of crime risk create at attracting criminal behavior.

In 1942, Shaw and McKay were able to offer a detailed account of the variations in crime in the city of Chicago. Their results suggested that over a three-decade period, changes in the social characteristics of people living in certain areas of Chicago were not determinants in explaining variations in crime rates. Instead, they argued, the situational persistence of crime emerged from a series of factors of criminogenesis converging at these areas (Shaw & McKay, 1942). At the time, this theory could not be demonstrated or replicated in any other study area outside of Chicago. In their works, Shaw and McKay (1942) discussed how rings of poverty are generators of criminal opportunity for new offenders. They theorized that urban areas acted like a "super-organism comprising a collection of sub-communities based around ethnic background, socioeconomic class, occupation, etc. (p. 5)" (Wortley & Mozerolle, 2013). Through their research, they were able to demonstrate how the migration of individuals from one community to another did not translate into a displacement of delinquency. These findings revolutionized the conventional wisdom on offender's individual characteristics to a theory of places.

As Caplan and Kennedy (2016) noted, Shaw and McKay's narrow focus on local group characteristics and cultural values missed the opportunity to include community characteristics and features of the landscape as major generating factors of criminal behavior within communities. With this objective in mind, the current study brings together the theoretical frameworks of social disorganization and environmental criminology to study how unique contexts of inequality and crime risk impact the persistence of violent crime outcomes at the neighborhood level.

Over the last decades, improved access to police records and multi-purpose municipal databases have allowed researchers and analysts to empirically demonstrate how the juxtaposition of land uses and transport networks shapes the backcloth on which crime occurs (Brantingham & Brantingham, 1995). As suggested by Brantingham and Brantingham (1995), "Particular types of land use like bars, fast food restaurants, nightclubs or restaurants are criminogenic because of the volume of people they attract, and sometimes, because of their activities, and that their juxtaposition with other land uses can affect the crime rates of entire neighborhoods" (p. 5). As a result, scholars have strived to identify the relationship between specific aspects of the built environment or urban design in connection with variations in crime rates across communities (Weisburd, Groff & Yang, 2012). As noted by Caplan and Kennedy (2016), the former "fixation on the actors in crime rather than a consideration of them in the spatial context in which they operate, has persisted in crime research until recently" (p. 3). Thus, the recent major shift in criminological research from the study of individual offenders to the study of places.

The Origins of the Environmental Perspective

Environmental criminology has rapidly evolved over the last century and has been influenced by different disciplines, including sociology, political science, demography, and economics. The environmental theoretical perspective is based on three general premises: how the immediate environment affects behavior, the non-randomized distribution of crime, and the existence of crime patterns (Wortley & Mozerolle, 2013). Three basic dimensions co-exist on the study of crime and place at three differentiated levels of analysis; namely, the macro, the meso, and the micro levels.

The macro-level analytical approach refers to the study of the distribution of crime among large geographical areas, such as countries or other sub-national units of analysis (Wortley & Mozerolle, 2013). In the late 1820s, André-Michel Guerry and Adolphe Quetelet debuted as the first researchers to analyze crime distribution using national statistics. They were among the first to use maps to illustrate the distribution of crime in France (Wortley & Mozerolle, 2013). Their maps included a detailed account on how socioeconomic factors like poverty and education level compared against the location of crime incidents across France's provinces. They found that crime was not equally distributed and that certain types of crime were more prevalent in certain regions. For instance, they were able to spatially demonstrate how the rich, living in the north of France, were at higher risk of being victimized by property crimes, while the poor southern regions were predominantly affected by violent crime incidents (Weisburd, Groff & Yang, 2012).

Based on these findings, they argued that poverty was not the main force driving crime incidents but the opportunity created by the wealthy that led to higher crime rates. As Quetelet (1835) suggested, contexts of great inequality between the poor and the wealthy provoke passions and create temptations of all kinds, referring to the effect that inequality has on crime patterns as a result of the spatial coexistence of disadvantaged and wealthy individuals. It wasn't until a century later that this movement took hold in the United States, with the works of Park et al. (1929), and Shaw and McKay (1942). Their research marked the beginning of the Chicago school, whose research led the way in the search for crime patterns across community environments in the city of Chicago.

The study of micro-level units of analysis focuses on the study of specific elements of the immediate environment and how these affect the behavior and decisions of individuals (Wortley & Mozerolle, 2013). In early 2010, Rutgers scholars Joel Caplan and Leslie Kennedy pioneered in the development of Risk Terrain Modeling (RTM), a micro-level technique that "paints a picture" of places that are statistically more likely to experience a criminal event based on a pool of environmental factors. RTM is an approach to spatial risk assessment that articulates the environmental backcloth for crime by layering the spatial influences of multiple risk factors (Caplan, Kennedy & Miller, 2011). As noted by Kennedy et al. (2012), crimes do not necessarily tend to occur at places with motivated offenders, suitable victims, and no capable guardians; instead, as they argue, it is the juxtaposition of these elements with “enabling places” that leads to higher rates of criminal events. In line with this argument, Wortley and Mozerolle (2013) argued that offenders don’t commit crimes all the time or indiscriminately; instead, they commit crimes infrequently and only under certain, favorable conditions. This approach can help police authorities and other stakeholders to identify locations where the risk of crime will increase if certain conditions are met (Kennedy, Caplan & Piza, 2012).

According to Emig et al. (1980), crime analysis can be defined as a set of systematic, analytical processes that provide timely, pertinent information about crime patterns and crime-trend correlations. A set of techniques based on the use of police reports articulate the response to particular crime problems. Through crime analysis, police investigators and other stakeholders obtain valuable information on deployment strategies, evaluation, and crime prevention (Wortley & Mozerolle, 2013). Particularly, the study and development of crime prevention strategies has experienced an extraordinary surge over the last few decades, as scholars and practitioners search for new strategies to prevent crime before it happens. As Clarke (1997) suggests, opportunity-reducing measures can “make crime more difficult and risky, or less rewarding and excusable as judged by a wide range of offenders” (p. 4). Similarly, Kennedy and Van Brunschot (2009) argue that the probability of crime can be reduced through targeted responses that make criminal offenses more “hazardous” to commit. Thus, there is increased interest in identifying the specific factors attracting or generating risk in certain places to develop targeted situational strategies aimed at reducing criminal opportunity.

Environmental criminology

As previously noted, the spatial characteristics of crime have continued to be explored since the early works of Guerry and Quetelet. This has resulted in the emergence of the field of environmental criminology, an area of research that studies the spatial and temporal characteristics of crime. Environmental criminology usually comprises the study of three major theories: routine activities theory (RAT) (Cohen & Felson, 1979), rational choice theory (Cornish & Clarke, 1986), and crime pattern theory (Brantingham & Brantingham, 1993).

Brantingham and Brantingham (1981) theorized that crime occurs when four things take place: a law, an offender, a target, and a place, all of which are characteristic of the so-called four dimensions of crime. They presented this theory when stating the following: "Without a law there is no crime. Without some object, target, or victim, there is no crime. Without a place in time and space where the other three come together, there is no crime" (Brantingham & Brantingham, 1981, p. 25). Therefore, the occurrence in time and space of a crime incident would be subject to the juxtaposition of a series of temporal and spatial elements that create criminal opportunities. In environmental criminology, the study of place as the fourth dimension of crime leads analysts to question what factors bring the offender and the target together at a crime site (Brantingham & Brantingham, 1981).

The routine activities theory (RAT) advanced by Cohen and Felson (1979) suggests that it is the combination in space and time of three basic dimensions: motivated offenders, suitable targets, and the absence of capable guardianship that lead to "predatory" crimes. They further explain that the absence of any of these elements will be enough to prevent the occurrence of a criminal incident. For example, criminal opportunities are more likely to emerge at places where general, routine activities (e.g., work and school) converge with these three elements. In this sense, it is widely accepted that crime incidents are not equally distributed in time or space, but instead, these tend to cluster around particular areas known as criminal hotspots (Wortley & Mozerolle, 2013). Also, criminogenic features tend to be absent from other places, known as cold spots. It is arguable that the presence or absence of crime can suggest patterns of criminal behavior. For example, residential robberies are more likely to occur at times of the day when occupants are out of their homes (Tseloni, Osborn, Trickett & Pease, 2002).

Building on the routine activities theory, the crime pattern theory advanced by Brantingham and Brantingham (1995) examines daily behavior patterns through activity spaces such as nodes, paths, and edges. These places are where people's daily routine activities take place but also where criminal offenders and potential victims tend to interact. For example, nodes can be described as the places where people spend most of their time (e.g. home), paths are the routes used to transit between nodes (e.g., a path going to work), and edges are the physical or social boundaries between these areas.

Additionally, places where routine activities take place can be influenced by the presence of crime generators and attractors (CGAs). The presence of CGAs creates unique criminogenic environments where victims gather for routine activities and/or criminals are attracted by criminal opportunities. For example, CGAs can include schools (Roncek & Faggiani, 1985), bars (Ratcliffe, 2012), hotels (Lebeau, 2011), parks (Groff & McCord, 2012), metro stations (Irvin-Erickson & La Vigne, 2015), and bus stops (Hart & Miethe, 2014). These places present a series of qualities that make them more attractive to display varying expressions of criminal behavior.

As Wortley and Mozerolle (2013) suggest, the combination of situational forces enable potential offenders to commit a crime, also known as precipitators, and the rational assessment of the existing criminal opportunities facilitate the occurrence of a criminal event. Therefore, a potential offender is more likely to commit a crime when a series of locational precipitators and opportunities exist.

Neighborhood effects on crime

As previously noted, crime analysis has mainly focused on three different levels of analysis, namely, the macro, meso, and micro levels. In recent years, micro level studies have become increasingly popular in the era of big data. Other studies, have opted to study contexts of crime at the neighborhood level (see Drawve, et al., 2016; Piza, Feng, Kennedy, & Caplan, 2016; Thomas & Drawve, 2018). Similarly, the current study sought to incorporate the lessons learned at the micro level with the RTM technique, and incorporate these findings to the study of neighborhood effects on crime. In doing so, this study presents a novel approach to identify risky environments (see Drawve et al, 2016; Thomas & Drawve, 2018) that allow to find associations between crime risk and unique societal contexts (e.g., socioeconomic inequality) that create environments that are conducive to criminal activity.

To better understand how different contexts of criminal risk vary across neighborhoods, it is important to refer to the early ecological arguments of Park, Burgess and McKenzie (1925). According to Burgess' Concentric Zone Model, a typical American city is organized in differentiated areas or zones. By observing Chicago's urban patterns, Burgess et al. (1925) explained how different areas exist within cities, and each present differentiated "economic and cultural groupings." These so-called zonal groupings are, grosso modo, the central business district[10], the zone in transition, the zone of working people's homes, the residential zone, and the commuters' zone (Park et al., 1925).

In their account of Chicago's urban organization, Burgess et al. (1925) described the existence of a multiplicity of social groups with their different patterns of life derived from the intricate segregation and isolation of divergent economic groups. As they suggested, these groups can live in widely separated and sometimes conflicting worlds. More importantly, Burgess and Park warned about the dangers of social disorganization and rapid urban expansion as factors leading to an increase in crime, vice, and disorder. Therefore, in their popular description of America's urban subdivisions and social structure, Park et al. (1925) introduced the idea of differentiated social groups living in sometimes segregated zones and how these groups co-exist within a typical urban context. This description offers a unique account on the dangers of what Park and Burgess referred to as "conflicting worlds" between segregated social groups within the same city.

Even though this theory might have helped to explain how American cities were historically divided, these subdivisions described by Park and Burgess don't necessarily reflect how American cities nowadays are organized and are much less the urban patterns of other world cities. As noted by Judd and Simpson (2011), "today's cities exhibit different patterns of development, economics, politics, culture, society, and government from the manufacturing-based city of the early twentieth century" (p. 356). This criticism explains the difficulties in replicating Park and Burgess's model in other cities within the United States and in other countries.

[10] "The Loop" in reference to Chicago's central business district

Building from the early works of Park et al. (1925), Shaw and Mckay (1942) challenged the existing theories focused on the role of "individuals" to explain crime with a theory of "places" that are conducive to criminal activity. The advancements brought by the social disorganization theory described how the lack of social cohesion can increase the likelihood of violence and crime. As Shaw and Mckay suggested, the locational persistence of three key factors – low economic status (e.g., poverty and substandard housing), ethnic heterogeneity (e.g., cultural and racial), and residential mobility – undermine social controls, leading to an increase in delinquency rates. In low-income areas, where the level of deprivation and frustration is higher, the probability of victimization dramatically increases, fueled by a lack of opportunities. They captured this argument when stating, "Crime may be regarded as one of the means employed by people to acquire, or to attempt to acquire, the economic and social values generally idealized in our culture" (p. 439). In this sense, they suggested that people have improved, at least temporarily, their social and economic status through criminal activity. In this scenario, the use of "unconventional ways" to secure material goods becomes embedded in the urban culture of the poor who lack the necessary opportunities to acquire these values by conventional means.

More recently, Sampson (2012) analyzed the spatial clustering of so-called socially disadvantaged neighborhoods and the continued presence of crime in these urban contexts across Chicago's communities. As Sampson (2012) noted, "Disadvantage is not encompassed in a single characteristic but rather in a synergistic composite of social factors that mark the qualitative aspects of growing up in severely disadvantaged neighborhoods" (p. 100). He referred to neighborhood characteristics like poverty, inequality, mobility, or structural density, and how these environments create unique contexts for crime. These ecological patterns are common to many cities and, according to Sampson (2012), extend across multiple ecological units of analysis ranging from census tracts to metropolitan areas and even states.

In his analysis, Sampson repeatedly analyzed the effect of inequality on Chicago's communities, in particular, the notorious income gap between white and black residents. According to his research, a typical black community resident earns on average \$12,276, while a resident of one of Chicago's white communities earns on average \$42,508. A very significant gap illustrates the existing social and ethnic segregation across neighborhoods in the city of Chicago. However, apart from this descriptive analysis of income inequality, Sampson's approach to inequality relies essentially on different dimensions of racial inequality, unemployment, and poverty rates across Chicago's communities. It does not account for patterns emerging from varying degrees of income inequality (regardless of race) and their effect on the variation of violent crime rates across neighborhoods.

The current study closes this theoretical gap by empirically testing the effect that unique contexts of inequality, as measured by the Gini index, and crime risk have on explaining the spatial distribution of violent crime rates across neighborhoods in the cities of Bogotá, Chicago, and Paros. It is, nonetheless, worth mentioning Sampson's contribution to the literature on the effect of racial inequality on violent crime. According to the racial invariance thesis, "Racial segregation by community differentially exposes members of minority groups to violence-inducing and violence-protecting social mechanisms, a process that explains black-white disparities in violence" (Sampson, 2012, p. 248). An argument that is revisited in detail in Chapter 5 in Chicago's case study.

Identifying Contexts of Crime Risk

For decades, a central question in the study of crime and place has dealt with finding a way to measure risk and criminal opportunity. As Ferraro (1995, p. 21) suggests, "measurement is the base of all science," and crime risk is not an exception. A myriad of studies have referred to the study of "perceived risk" on the basis of individual characteristics and other ecological variables (see Park et al., 1925; Shaw & McKay, 1942; Ferraro, 1995; Sampson, 1985). However, these studies do not account for the varying effects that the built environment has in attracting and generating criminal behavior. For example, walking alone at night through a dark alleyway can increase the risk of victimization because of the combined spatial influences of an alleyway (e.g., fewer people) and poor lighting (e.g., reduced visibility). As a result, places where these two physical features collocate will present a greater risk for potential victims while creating an opportunity for offenders looking for their next victim. The various risks presented by these places are independent of the victims' individual characteristics, as these become secondary given the qualities of these spaces that are conducive to criminal activity.

In this sense, differentiated risk levels can be assigned to certain features of a landscape in order to model their relative importance in attracting criminal behavior, allowing us to forecast the location of future crime incidents. Caplan (2011) captured this argument when noting that, "It is the spatial influence of criminogenic factors on their environments that enables motivated offenders and increases the likelihood of illegal activities at certain places" (p. 59). As a result, modeling the spatial influences of the built environment allows us to identify spatial vulnerabilities and measure the risk of future crime.

According to the theory of risky places (Kennedy et al., 2015; Caplan & Kennedy, 2016), all places can be deemed to be risky, but some are riskier than others. The reason for these variations is the presence or absence of criminogenic features at certain locations as compared to others. As a result, the theory of risky places posits that crime emerges in places that present high levels of vulnerability based on the combined spatial influences of a series of criminogenic features. As Caplan and Kennedy (2016) note, risky places are a product of vulnerability, based on the spatial influences of the built environment that attract criminal behavior, and exposure to crime, measured as a concentration of past crime incidents. The presence of vulnerable spaces can be articulated through RTM, while places presenting a concentration of incidents can be measured using hotspot mapping. As a result, the vulnerability-exposure framework (Caplan & Kennedy, 2016) posits that risky places will emerge at locations presenting contexts of spatial vulnerability, processes of near repeat victimization, and the threat of past exposure to crime. Overall, the effect of risk on crime is a function of differential vulnerability and exposure throughout the landscape. As Kennedy et al. (2015) note, it is by incorporating the risk that past experience presents at certain vulnerable places that the location of future incidents can be effectively forecasted.

The RTM technique allows to identify contexts of spatial vulnerability by modeling the spatial influences of the built environment at creating unique behavior settings for criminal activity. In 2013, the Rutgers Center on Public Security developed the Risk Terrain Modeling Diagnostics (RTMDx) tool, a software application that automatizes the use of RTM. Unfortunately, the current RTMDx framework does not account for the effect that unique social contexts create at enabling or attenuating the spatial influences created by the built environment (see Thomas & Drawve, 2018). This is due to the current limitation by which RTMDx requires the use of micro level data to conduct RTM analyses. These limitations are partially due to the fact that census data tends to be available at higher orders of aggregation (e.g., neighborhood, county, city, etc.) making it more difficult to be included under the existing RTMDx framework.

To overcome these limitations, Drawve et al. (2016) proposed the aggregate neighborhood risk of crime (ANROC) approach to incorporate social structure data into the RTMDx framework. This complemented the existing RTM process that identifies the risk associated with the built environment with the influence of social and physical characteristics of entire neighborhoods (Drawve et al., 2016). The current study further expands previous research works by Drawve et al. (2016) and Thomas and Drawve (2018) by proposing the study of unique contexts of crime risk and socioeconomic inequality to explain the distribution of violent crime rates across neighborhoods in three different world cities.

Conclusion

The study of crime and place has undergone a series of major transformations over the last centuries. From the early works of Guerry and Quetelet in France to the research of Park and Burgess and of Shaw and McKay in Chicago, the study of the spatial and temporal characteristics of crime has dramatically shaped the way in which crime research is conducted. The ecological school has played an essential role at identifying the presence of unique social contexts to explain the distribution of crime across communities and across jurisdictions. However, ecological theorists (see Park et al., 1925; Shaw & McKay, 1942; Sampson, 1985) have missed the opportunity to account for the spatial influence of the physical environment as a major contributing force driving expressions of criminal behavior.

Meanwhile, the area of research of environmental criminology (see Brantingham & Brantingham, 1993, 1995; Cohen & Felson, 1975; Cornish & Clarke, 1986) has proposed different theories that acknowledge the importance of the built environment and routine activities as major factors explaining the distribution of crime. Building from early works in environmental criminology and spatial analysis, the theory of risky places (Caplan & Kennedy, 2016) supports the interactive effect of the contexts of spatial vulnerability and past crime exposure in modeling the spatial dynamics of crime. These contexts of spatial vulnerability can be identified through the use of risk terrain modeling (RTM), an approach to spatial risk assessment that models the spatial influences of the built environment in creating unique behavior settings for criminal activity.

To date, the areas of research in environmental criminology and social disorganization have remained separated, with few studies including these two large theoretical frameworks into RTM research (see Drawve et al. 2016; Piza et al. 2017; Giménez-Santana, et al., 2018; Thomas and Drawve, 2018). The current study proposed testing how unique contexts of socioeconomic inequality and crime risk, measured using ANROC and calculated with RTM, can explain the spatial distribution of violent crime rates across neighborhoods in Bogotá, Paris, and Chicago. In doing so, this research study sought to continue expanding the extant literature on neighborhood effects on crime by incorporating the areas of research of environmental criminology, spatial analysis, and the study of risky environments.

CHAPTER 4: RESEARCH METHODS AND HYPOTHESES

> *"Certain features of the environment will create behavior settings with exceptionally strong likelihoods for criminal events. RTM articulates these vulnerable places and advances our understanding of the spatial dynamics of crime."*
>
> \- Caplan and Kennedy, 2016

The current chapter presents the research methods utilized to test this study's research question across case studies for Bogotá, Chicago, and Paris. Then, the main hypotheses of this multi-jurisdictional study are revisited in detail. As previously discussed, this study analyzes the relationship between unique contexts of crime risk and socioeconomic inequality on the spatial distribution of violent crime victimization rates across neighborhood-environments. The presence of neighborhood contexts of socioeconomic inequality was tested using the Gini indicator for income inequality for each community across all three case studies. The data for this indicator were directly obtained from each country's statistical office. Then, to model the spatial distribution of crime risk, this study assessed the distribution of varying micro-level contexts of physical risk utilizing the risk terrain modeling (RTM) method. As noted by Caplan and Kennedy (2016), RTM allows identifying spatial vulnerabilities to crime that represent the spatial influences of environmental factors across places. To assess the spatial distribution of micro-level crime risk, separate RTM analyses were conducted for each case study in this dissertation.

Moreover, the current study used the risk terrain modeling diagnostics (RTMDx) software (Caplan & Kennedy, 2013), a program that automatizes the analytical steps necessary to conduct RTM analyses. RTMDx applies a set of precise statistical analyses

(Caplan, Kennedy, & Piza, 2013) to find spatial associations between features of the built environment and the distribution of crime events. Based on RTM's tabular and cartographic outputs, calculations can be made to create ANROC measures (Drawve et al., 2016; Thomas & Drawve, 2018), thus depicting the spatial distribution of crime risk across neighborhood environments.

In sum, the current study's analytical approach to identifying neighborhood-level contexts of crime risk comprised three basic steps: (1) assessing the presence of spatial vulnerabilities at the micro-level using RTM, (2) analyzing the spatial influences of a series of features of the built environment on the distribution of violent crime events utilizing the RTMDx[11] software, and (3) calculating neighborhood-level contexts of crime risk with the ANROC measure.

Risk Terrain Modeling

In 2010, risk terrain modeling (RTM) was developed by Caplan and Kennedy (2010) at the Rutgers Center on Public Security. This technique combines "key concepts from environmental criminology and spatial analysis, applied to the study of spatial vulnerabilities on crime outcomes" (Caplan & Kennedy, 2016, p. 11), thus allowing for the identification of micro-level locations presenting a high risk (i.e., spatial vulnerability) of victimization based on the spatial influences of a series of environmental factors.

The RTM method is rooted in the principles of environmental criminology (Wortley & Mazerolle, 2008) and risk assessment (Kennedy & Van Brunschot, 2009),

[11] RTM analyses can also be manually conducted by following the 10 steps of the risk terrain modeling (see Caplan and Kennedy, 2016)

allowing one to evaluate the influences of the physical environment's crime attractors and generators (Brantingham & Brantingham, 1995). As noted by Caplan and Kennedy (2016), "RTM paints a comprehensive picture of the spatial dynamics of crime" (p. 90). It does so by modeling the spatial influences of an array of ecological features to determine the spatial association between these locations and past exposure to crime events. As discussed by Caplan (2011), understanding the spatial influence includes evaluating the relative effects of distance or the density of criminogenic features on crime occurrence. The RTM method allows one not only to identify the spatial distribution of risky places but also to weigh their relative risk on the dependent variable (i.e., violent crime event locations).

RTM's analytical approach is supported by the theory of risky places (Kennedy & Caplan, 2012; Caplan & Kennedy, 2016), which postulates that the combined effect of spatial vulnerability (i.e., spatial influences that emanate from the built environment) and exposure to past crimes (e.g., areas with a concentration of past crime incidents) can yield actionable intelligence in the location of crime incidents. As noted by Kennedy et al. (2016, p. 3) in reference to the vulnerability exposure framework, "incorporating exposure into a spatial vulnerability model helps to reduce the effects of false positives by considering the risks that past experience with crime present at vulnerable places," thus indicating that crime is more likely to emerge at micro-level places that present a combination of past exposure (e.g., crime hot spots) and spatial vulnerability (e.g., environmental risk).

In 2013, Caplan and Kennedy developed the first iteration[12] of the RTMDx software (Caplan & Kennedy, 2013) at the Rutgers Center on Public Security. RTMDx automatizes the RTM process to produce an output list of environmental risk features and

[12] In late 2017, the Rutgers Center on Public Security released a new version of the original RTMDx software.

their relative spatial influences on the outcome event (see Caplan, Kennedy, & Piza, 2013). This analytical process applies a precise set of statistical tests (see Caplan et al., 2013) to weigh and evaluate the relative importance of different risk factors that influence crime outcomes. First, the software builds an elastic penalized regression that assumes a Poisson distribution of events by using the cross-validation technique. Then, the model is further simplified via a bidirectional stepwise regression process that assumes a Poisson and a negative binomial distribution model to determine the "optimal fit" for the final RTM. This process calculates the Bayesian Information Criteria (BIC) of different candidate models by adding risk factors and re-measuring the BIC score at each iteration. As a result, the model with the lowest BIC score is selected as the "best candidate model."

The resulting RTMDx output offers two main sets of information. The first is tabular data, and the second is the cartographic output for each significant risk factor within the final RTM model. The tabular output includes a relative risk value (RRV) for each significant risk factor that allows for comparisons to be made regarding the relative weight of risk factors within the model. These values are obtained by rescaling factor coefficients to obtain the relative weight of each risk factor. Lastly, tabular data offers information on the optimal operationalization and distance extent of spatial influences with the outcome event. As a result, RTM outputs offer a depiction of the spatial distribution of high-risk places throughout the study area. The distribution of high-risk places can be symbolized by displaying, on a map, all micro-level places (i.e., map cells) with a relative risk value (RRV) of two standard deviations over the mean (see Kennedy et al., 2016).

The data inputs that are needed to conduct an RTM analysis can be summarized using the 10 steps to risk terrain modeling (see Caplan & Kennedy, 2016). This analytical process requires choosing an outcome event, a study area, and a time period. In the next steps, potential risk factors are identified, and spatial data is obtained, allowing one to map the spatial influence of risk factors on the spatial distribution of crime events. Lastly, all significant model factors are selected, weighted, and combined. The results obtained through RTM are then disseminated across all relevant stakeholders (e.g., patrols, city hall officials, general public, etc.).

In this sense, the current study analyzed the underlying spatial attractors of violent crime incidents (step 1) within the geographic boundaries of the cities of Bogotá, Chicago, and Paris (step 2) during the 2012 calendar year (step 3). A comprehensive list of the best available risk factors was selected for each geographical location (step 4), and spatial data were collected and verified (step 5) to ensure content and construct validity. For instance, risk factor data missing records were reviewed to ensure data completeness. In steps 6 to 9, all final data were operationalized within the RTMDx framework to map the spatial influences of a set of physical features on the distribution of violent crime events. The final RTMDx output offers a snapshot with all model factors that create unique physical micro-level environments that are conducive to criminal activity across these three study settings. In Chapter 8, a discussion on the policy implications of this study offers different avenues to disseminate (step 10) the spatial intelligence obtained through RTM and ANROC with potential organizations and other relevant stakeholders.

Average Neighborhood Risk of Crime

In the next step, the aggregate neighborhood-level risk of crime (ANROC) is calculated using RTM's data outputs. This approach was initially developed by Drawve, Thomas, and Walker (2016) in a study conducted on neighborhood characteristics on violent crime in the city of Little Rock in Arkansas. According to Drawve et al.'s (2016) research findings, a positive and statistically significant association exists between the ANROC measure and socioeconomic disadvantage with neighborhood levels of violent crime victimization in Little Rock, Arkansas. As they suggested, the existing RTM framework is currently limited to the study of micro-level risks, a level of analysis presently constrained by a lack of social indicators. In a more recent study, Thomas and Drawve (2018) tested at the block-group level the influence of structural disadvantage and the ANROC measure for crime risk on the distribution of assault incidents. According to their findings, neighborhood physical and social characteristics are integral to understanding variations in assault victimization levels across neighborhood environments.

Building on previous research by Drawve et al. (2016) and Thomas and Drawve (2018), the current study proposes the utilization of the ANROC approach to measure neighborhood contexts of crime risk across communities in the cities of Bogotá, Chicago, and Paris. This approach is simple and straightforward. It starts by calculating the average risk value for each raster cell in a neighborhood. It is important to note that RTM's unit of analysis consists of equally-sized raster cells that extend over the entire study area, and that each of these cells is assigned a relative risk score ranging from 1 (lowest/no risk) to x (highest risk). The process begins by calculating RTM cells' centroids using GIS software such as ESRI's ArcGIS or QGIS software suites. Then, all centroids that fall within the boundaries of a neighborhood are averaged to form the average neighborhood measure. The resulting ANROC measure offers a depiction of the average neighborhood level of crime risk across neighborhoods in a given jurisdiction.

In the last step, a control variable for neighborhood area size is included as part of this research study. Given that the ANROC measure offers an aggregate depiction of risky places at the neighborhood level, controlling for the total land area for each neighborhood becomes a necessary additional step for this analysis. For instance, large neighborhoods present a small number of high-risk places as well as a number of low-risk locations, which can result in a moderate-to-low ANROC measure. This result can be misleading since averaging risk values washes out micro-level variations, inflating high-risk values in some locations. Similarly, a small neighborhood with widespread above-average risk places, could present an inflated ANROC measure for that neighborhood. For example, in the city of Chicago, neighborhood size ranges from 8 sq. miles to just 90,000 sq. ft. Therefore, to control for variations arising from neighborhood total land size across geographies, a control variable is included during the analyses conducted in all three case studies in this dissertation.

Research Question and Hypotheses

As seen in Chapters 2 and 3, a vast body of literature supports the role that neighborhood-level social and physical play correlates with explaining changes in the rates of victimization across community environments. This theoretical background raises the research question of this dissertation that seeks to test the combined effect that unique social and physical environments present when explaining the spatial distribution of violent crime rates. Therefore, the main research question is: "To what extent do the combined effects of unique contexts of neighborhood-level crime risk and socioeconomic inequality influence the spatial distribution of violent crime rates across neighborhoods?" Based on this research question, the following hypotheses were developed:

Hypothesis #1 (H1): *The presence of unique contexts of crime risk and socioeconomic inequality is associated with an increase in violent crime victimization rates across neighborhoods within different cities while controlling for neighborhood area size.*

Hypothesis #2 (H2): *The distribution of neighborhood-level violent crimes rates is dependent on the spatial allocation of unique contexts of physical and social risk across community environments in different cities while controlling for neighborhood area size.*

As previously noted, the extant economic literature on crime (see Blau & Blau, 1982; Kelly, 2000; Fajnzylber et al., 2002; Soares, 2002; Hipp, 2007; Choe, 2008; Ousey & Lee, 2013; Enamorado et al., 2014) has identified the presence of varying contexts of socioeconomic inequality with an increase in victimization rates. Similarly, previous works on neighborhood-level crime risk (see Drawve et al., 2016; Thomas & Drawve, 2018) have found a positive association between neighborhood contexts of crime risk and socioeconomic disadvantage with an increase in victimization rates across communities.

To test these hypotheses, the current dissertation analyzes the physical and social determinants of victimization rates across communities in the cities of Bogotá, Chicago, and Paris. It is important to mention the presence of varying nuances across these jurisdictions. For instance, the categorization of what constitutes a violent crime event differs across countries. As noted by the UNODC[13], comparing international crime statistics present a series of challenges due to differences in the definition of crime types, changes in reporting methods, and socio-political contexts across different countries. Therefore, each case study in this analysis presents a unique account on victimization based on the local definition of what constitutes a violent crime event. Additionally, Paris' case study includes a variable for neighborhood-level unemployment rates that to measure the impact of this additional social variable in the distribution of violent crime victimization rates. Therefore, each analysis will offer different nuances when developing these hypotheses.

Furthermore, based on the attracting qualities that neighborhood-level physical and social contexts present individually on the distribution of victimization rates, the following sub-hypotheses are formulated from H1:

H1.1: Neighborhood contexts of physical risk are associated with an increase in violent crime victimization rates across neighborhoods.

H1.2: The presence of unique contexts of socioeconomic inequality is associated with an increase in violent crime victimization rates across neighborhoods.

The results from the following three case studies allow testing whether or not the spatial distribution of violent crime victimization rates across neighborhoods is dependent on the presence of unique contexts of crime risk and socioeconomic inequality. This novel approach in the study of environmental risk and criminal opportunity is enhanced by

[13] http://www.unodc.org/unodc/en/data-and-analysis/Compiling-and-comparing-International-Crime-Statistics.html

combining the social and physical characteristics of entire community environments to explain the situational persistence of crime and violence across communities in three largely distinctive world cities.

Concluding remarks

In the next three chapters of this dissertation, the hypotheses of this study are tested through the examples of three major cities located in largely different world regions. These regional differences allow to test for variations across neighborhood environments between these three case studies while using the same analytical approach across geographies. Thus, testing the capacity of RTM and the ANROC measure to identify contexts of physical risk at the community level, and to determine if these contexts of crime risk in juxtaposition with unique neighborhood environments of socioeconomic inequality are associated with an increase in violent crime victimization rates.

CHAPTER 5: THE CASE FOR BOGOTÁ, COLOMBIA

"The strata have a georeferenced component attached to them, but this one is not linked to the administrative divisions of the city. Instead, it is a notion with two distinctive realities, one is social and the other geographic. Its social aspect is based on a hierarchical definition, while its geographic component refers to a place."

- Consuelo Uribe-Mallarino

In the 1990s, the city of Bogotá experienced one of the highest rates of violent crime victimization in the world (Gaviria et al., 2010). A situation that was fueled by a long-standing armed conflict between government forces and drug trafficking groups; aggravated by the massive migration of internally displaced people who fled war-torn rural areas into Colombia's capital city (Beckett & Godoy, 2010). The situation rapidly worsened by the lack of public services and proper public transportation, increasing tensions within the most vulnerable social groups of the city. According to Moser et al. (2005), Bogotá's descent into extreme violence and crime was caused by the loss of values and traditions, the lack of credibility on a fair judicial system and police forces, and the presence of gang members and other organized criminal organizations. A situation that dramatically changed in the last few decades with the implementation of policies directed at reducing crime and violence in Bogotá (Moser et al., 2005). For instance, while in the year 1994 the homicide rate was estimated at 80.87 deaths per 100,000 people, the same rate experienced a decrease to just 16.62 deaths per 100,000 people during the year 2012, more than a 400% decrease (Colombia National Police, SIEDCO 2017).

The city of Bogotá presents, as other Latin American cities do, a clear pattern of spatial segregation across its urban environment (Thibert & Osorio, 2014). Yet what makes

Bogotá stand out when compared to other large Latin American cities is its current use of a socioeconomic stratification system that spatially categorizes Bogotá's built environment into different stratum. As noted by Thibert and Osorio (2014), a segregation system "reinforced by a spatial socioeconomic stratification system used to target subsidies towards the poor, which effectively identifies certain areas of the city as poor, middle-class or rich" (p. 1319). As a result, offering an objective measure on the spatial distribution of socioeconomic groups across Bogotá's geography, bringing to light the intense degree of urban segregation that exists in the city.

The city of Bogotá offers a unique opportunity to test the main hypothesis of this study, as it presents both, high levels of inequality and violent crime victimization rates within its borders. According to a survey conducted in 2012 to 1,500 people in Bogotá, 72% of respondents claimed that they perceived the level socioeconomic inequality to be high or very high (Encuesta sobre Percepción Ciudadana sobre la Desigualdad Urbana en Bogotá, 2012). These high levels of perceived socioeconomic inequality stress Bogotá's social context of accrued inequality. Thus, making Bogotá an ideal candidate to test how unique contexts of crime risk and socioeconomic inequality influence the distribution of violent crime rates across the city's neighborhoods.

In this first case study, Bogotá's violent crime problematic was first discussed from a historical perspective to better understand how social changes affected the city's spatial pattern of violent crime. As noted, this study offers a unique opportunity to assess the specific locational factors that attract and generate criminal opportunity within the city's border. Very few studies have analyzed the spatial distribution of crime in Colombia. Gaviria and Velez (2001) argued that Bogotá's richest households are at a higher risk of property crimes or kidnappings, while poorer Bogotans are more likely to be victims of homicides or been victims of domestic violence. Similarly, Llorente et al. (2001) found a connection between the presence of established criminal structures and the concentration of violent crimes incidents in certain parts of Bogotá. More recently, Giménez-Santana, Caplan and Drawve (2018) empirically demonstrated the micro-level spatial association between locations with a higher density of low stratum households and an increased risk of homicide and assault incidents in the city of Bogotá.

This study aims to fill the existing theoretical gap on the spatial association between unique contexts of socioeconomic inequality and crime risk with the presence of higher violent crime rates across the Bogotá's neighborhoods. Having this objective in mind, this relationship was empirically tested by analyzing Bogotá's 111 UPZs[14] geographic sub-divisions. For the purpose of this analysis, Bogotá's UPZs were operationalized as neighborhood units of analysis that extend throughout the city's geography. Data was obtained both, at the micro and neighborhood levels to test the hypothesis of this study. In other words, the presence of unique contexts of crime risk and socioeconomic inequality were tested to determine the association between these contexts and the variation of violent crime victimization rates across Bogotá's neighborhoods.

First, the relationship between neighborhood contexts of income inequality, as measured by the neighborhood-level Gini index, and the rate of violent crime victimization was tested for each unit of analysis. Then, the Risk Terrain Modeling (RTM) technique was utilized to identify, at the micro-level, those places presenting a higher risk of violent crime victimization. The next step consisted on building a neighborhood-level measure of

[14] Translated from Spanish as Property Zoning Units (In Spanish: Unidad Predial Zonal).

crime risk to determine the existing variations across Bogotá's neighborhoods. The Average Neighborhood Risk of Crime (ANROC) (see Drawve et al, 2016; Thomas & Drawve, 2018) was the approach employed to calculate the average level of risk ascribed to each neighborhood. Thus, allowing to compute both, the average risk of violent crime victimization and the average level of income inequality for each neighborhood in the city. These results were tested against the different rates of violent crime victimization for each neighborhood. This effectively permitted to empirically test how varying contexts of inequality and crime risk had an effect on Bogotá's neighborhoods violent crime rates.

Background

Bogotá's current social and spatial segregation is the result of decades of rapid population growth (Gaviria et Al., 2010). For instance, in 1938 the city's total population was approximately 330,000 or less than 5% of its current size (Thibert & Osorio, 2014). From the 1950s to the 1970s the city went through a period of spectacular population growth, becoming one of the fastest growing cities in the world (Yunda, 2017). During these years of unprecedented growth, the polarization between urban elites and rural migrants intensified as the spatial segregation between groups increased. This led Bogotá's social elites to move to the northern suburbs of the city where greater municipal services and work opportunities already existed; while low-skilled rural migrants moved to informal neighborhoods in the southern parts of the city characterized by a reduced access to municipal services, and a lack of proper public transportation to the central business districts (Yunda, 2017). As a result of these demographic changes, the city became "highly segregated, with large concentrations of wealth and poverty in few areas" (Thibert & Osorio, 2014, p. 1330).

As previously noted, the case for Bogotá is particularly relevant within the Latin American regional context because of its existing socioeconomic stratification system. The stratification of Bogotá's dwellings allows to spatially analyze the city's social segregation patterns across socioeconomic groups within the city's neighborhoods. In Bogotá, the level of socioeconomic segregation is considerably higher than that of other world cities like Paris; making inequality patterns more pronounced and increasing the distance between different social groups. According to a report from Bogotá's Planning Department (SDP)[15], social segregation is reinforced by the spatial clustering of residents in distinct areas, effectively dividing social groups across class lines.

Bogotá's local government is directly responsible for measuring and periodically re-assessing stratum levels in the city through its Permanent Committee on Stratification which is formed by local government officials, representatives from utility companies, and other local stakeholders. According to Colombia's statistics department (DANE)[16], the system of socioeconomic stratification is a mechanism that allows classifying people from different stratum levels or groups of people with similar social and economic characteristics, through the assessment of the physical characteristics of their dwellings, their immediate environment, and their urban context. It is important to note that the methodology used to calculate stratum level does not include any individual or group assessment on income level. Thus, making this measure a purely environmental assessment

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[15] http://www.sdp.gov.co/portal/page/portal/PortalSDP/actualidad-SDP-home/LAESTRATIFICACION-BOGOTA-DIGITAL.pdf

[16] http://www.sdp.gov.co/portal/page/portal/PortalSDP/InformacionTomaDecisiones/Estratificacion_Socioeconomica/QueEs

of Bogotá's dwellings on the basis of a series of locational and physical factors of the built environment.

As seen in Table 2, three major factors, namely physical characteristics of dwellings, the urban environment and the urban context; all constitute the basis for the existing socioeconomic stratification system in Bogotá. As a result, offering an ecological depiction of the built environment that is conducive to the level of socioeconomic development of entire neighborhoods. In this sense, dwellings located within lower stratum neighborhoods will lack access to proper roads or sidewalks, will not be paved and their façades will be unfinished or damaged, all of which can potentially generate unique contexts of criminal risk.

Table 2. Methodology used by local authorities to measure stratum level

<table>
<tr><th>Factors</th><th>Variables</th><th>Unit of observation</th><th>Unit of analysis</th></tr>
<tr><td rowspan="4">Dwelling Characteristics</td><td>Yard size</td><td rowspan="7">Side of City Block</td><td rowspan="7">Side of City Block or City Block</td></tr>
<tr><td>Type of parking</td></tr>
<tr><td>Status of façade</td></tr>
<tr><td>Door type</td></tr>
<tr><td rowspan="2">Urban Environment</td><td>Type of sidewalk</td></tr>
<tr><td>Type of street</td></tr>
<tr><td>Urban Context</td><td>Zoning / Land use</td></tr>
</table>

Source: DANE Bogotá

According to a 2012 survey conducted to 1,500 Bogotans on their perception of security, a 46% answered that they feel insecure in the city and 28% claimed to feel insecure in their respective neighborhoods (Encuesta de Percepción Ciudadana, 2012). This vast difference suggests that the perception of insecurity varies within Bogotá and that location matters on the way Bogotans perceive their close environment and their security. In a more recent iteration of the same survey conducted in 2017, new data was obtained on the perception of insecurity at the neighborhood-level while controlling for the socioeconomic group of the respondent (Encuesta de Percepción Ciudadana, 2017). According to this new survey, only 13% of Bogotans ascribed to a high-income group claimed to feel insecure in their neighborhood, while the figure doubled to 26% when middle-class citizens were asked about their perception of insecurity in their communities. Perhaps, and most notably, a staggering 49% of all low-income respondents indicated that they feel insecure in their neighborhood. Therefore, according to these survey respondents, not only location matters in Bogotá, but residential segregation across socioeconomic groups play a determinant role at explaining varying degrees of risk and insecurity within Bogotá's neighborhoods.

Since the 1990s, various efforts have been undertaken by Bogotá's local government officials to curb crime and violence outbreak in Colombia's capital city. In particular, the administrations of Mayors Antanas Mockus (1995 – 1997, 2001 – 2003) and Enrique Peñalosa (1998 – 2000, 2016 – incumbent) implemented a number of policies aimed at reducing crime and violence in the city. According to Moser et al. (2005), Bogotá transformed itself through the Mockus and Peñalosa's administrations by bringing changes to the public health system, reclaiming public spaces to improve security, and improving the city's criminal justice system. Indeed, as much as 49% of all Bogotans believed in the year 2012 that their criminal justice system was not effective at reducing crime, and 70% responded that the probability of a criminal offense to be sanctioned by law enforcement was low (Encuesta de Percepción Ciudadana, 2012). This environmental approach aimed at improving Bogotá's security by rehabilitating public spaces, gained public attention and became a success story. Nowadays, this social program is still transforming public spaces all over the city by reducing parking spaces to improve pedestrian access to sidewalks, and reconditioning parks to promote that people regain these places. As a result, the number of violent crimes decreased by 50 percent over six years (Moser et al., 2005). Therefore, suggesting that through the transformation of public spaces the city of Bogotá was able to effectively reduce criminality by applying a set of purely environmental approaches.

Data and Research Methods

The city of Bogotá in 2012, time of the current study, had a population of approximately 7.5 million people (DANE-SDP, 2012) living an area of approximately 384 sq. Km (approx. 148 sq. miles), of which 345 sq. Km (approx. 133 sq. miles) were legally or informally[17] urbanized (Encuesta Multipropósito para Bogotá, 2011). For the purpose of this analysis, only Bogotá's urban space was analyzed, excluding the city's surrounding rural areas[18]. To test the hypothesis to this case study, micro and neighborhood level data were collected from Bogotá's IDECA, SDP, DANE, the cadastral office, and FIP's crime data repositories. The primary objective of this analysis was to empirically determine if the presence of higher levels of income inequality and crime risk are spatially associated with higher violent crime rates across Bogotá's neighborhoods.

[17] Informal urbanization patterns are common in the Latin American region and refer to the illegal occupation of land by population at risk, mainly low-income groups, working on Bogotá's informal sector that can't otherwise access the legally established local housing market (Camargo Sierra and Hurtado Tarazona, 2013).

[18] Bogotá's surrounding rural areas are sparsely populated and present a very low percentage of all violent crime incidents.

First, the neighborhood-level crime rate for all 111 sub-divisions of Bogotá was calculated by dividing the total number of reported crimes for each neighborhood by each neighborhood's total population, and by then multiplying these results by 1,000 to obtain the final crime rate per 1,000 neighborhood residents. This calculation was performed for the calendar year 2013, and included all incidents for assault, theft and homicide incidents during that year. This data were facilitated by the Fundación Ideas para la Paz (FIP) and derives from FIP's calculations on primary-level data from the Colombian National Police. All records were initially geo-referenced using the WGS84 coordinate system.

Table 3. Descriptive statistics

	Obs.	**Mean**	**Std. Dev.**	**Min**	**Max**	**Skewness**	**Kurtosis**
Dependent variable							
Crime Rate 2013 (per 1,000 people)	111	7.22	12.66	0	88.54	3.93	20.88
Independent variables							
ANROC	111	9.10	6.32	1	42.33	2.28	10.98
Gini	111	45.5	6.51	36.6	58.7	0.45	2.01
Neighborhood Area (Sq. Km.)	111	3.70	1.66	0.81	7.75	0.57	2.65

Sources: Colombian National Police (2012; 2013); SDP-Bogotá (2011)

After a preliminary inspection of the descriptive statistics displayed in Table 3, the data suggested that neighborhood violent crime rates and ANROC measures had normality issues. For instance, 2013 violent crime rate data appeared to be highly skewed (3.93) and leptokurtic (20.88). As for the ANROC measure, the data also showed normality issues with a highly skewed (2.28) and leptokurtic (10.98) distribution. To induce normality, both variables were transformed using the square-root transformation method. The newly transformed 2013 Crime Rate measure ranged from 0 to 9.41 with a mean of 2.22 and a standard deviation of 1.52. As for the transformed ANROC measure, the variable ranged from 1 to 6.51 with a mean of 2.87 and a standard deviation of 0.95.

Then, 2012 violent crime incidents were operationalized using RTM to calculate, along with other environmental risk factors, the relative risk of violent crime victimization across Bogotá's neighborhoods. Moreover, 2013 violent crime rates were operationalized as the dependent variable to test the effect that unique contexts of criminal risk and inequality have on Bogotá's neighborhood crime rates. As seen in Table 3, the neighborhood-level crime rate in 2013 ranged from none to 88 deaths per 1,000 people, denoting a high level of variation across Bogotá's neighborhoods.

Table 4. Correlation matrix

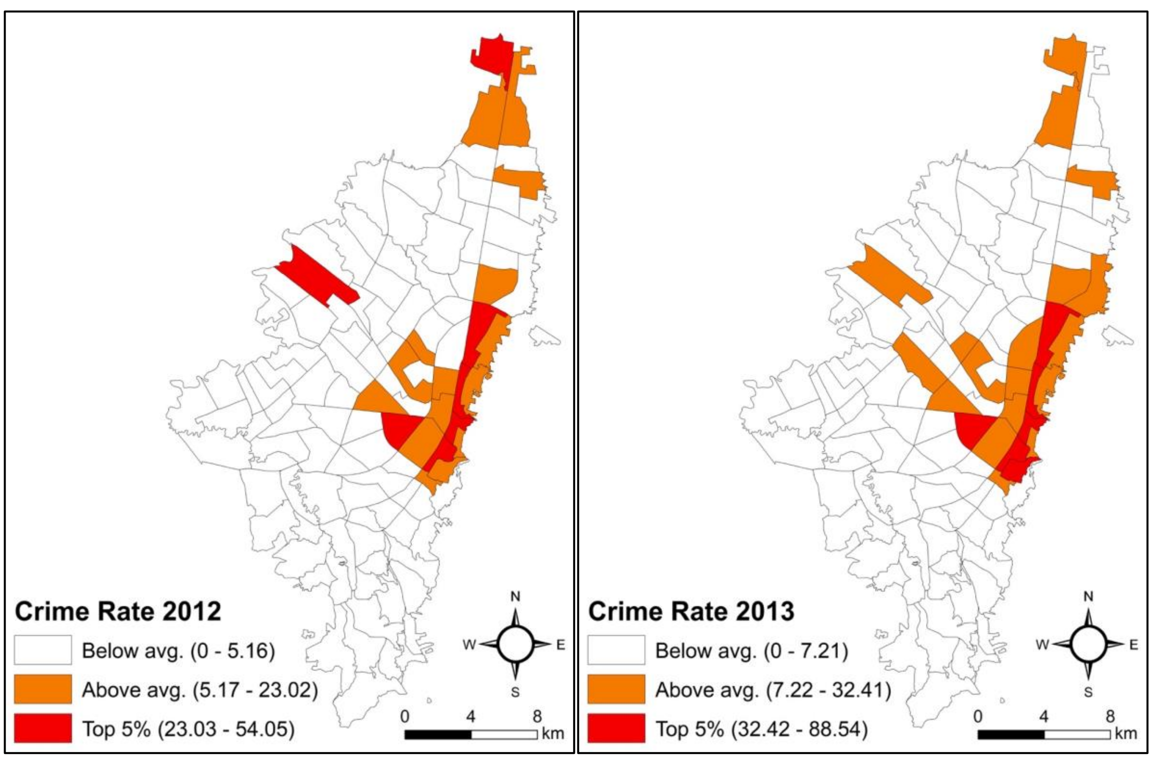
	2013 Crime Rate	ANROC	Gini	Neighborhood Area
2013 Crime Rate	-	0.494***	0.473***	- 0.25**
ANROC		-	0.188*	- 0.33***
Gini			-	- 0.07
Neighborhood Area				-

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

To establish the association between the two independent variables, 2013 violent crime rates, and the control variable for neighborhood area size, a correlation matrix was calculated. The results, as seen in Table 4, suggest that 2013 crime rates are positively correlated with the two predictive measures, namely crime risk and inequality. Furthermore, the positive correlation between the two predictor variables reinforces the hypothesis of the current study, as these variables both have significant and positive relationships with 2013 crime rates. Lastly, both independent variables appeared to be highly correlated with the control variable for neighborhood land area.

By taking a closer look at 2012 and 2013 violent crimes rates, it becomes apparent that violent crime tends to occur in near identical locations between the two years. These variations can be easily visualized in Figure 2, in which violent crime rates are categorized according to their spatial distribution in three distinct sub-groups: under the mean, mean plus two standard deviations and two standard deviations to the maximum. This study applied the same symbology and spatial distribution criteria to all its maps to simplify data analysis and comparisons across different measures.

Figure 2. Comparing neighborhood violent crime rates in Bogotá between 2012 and 2013



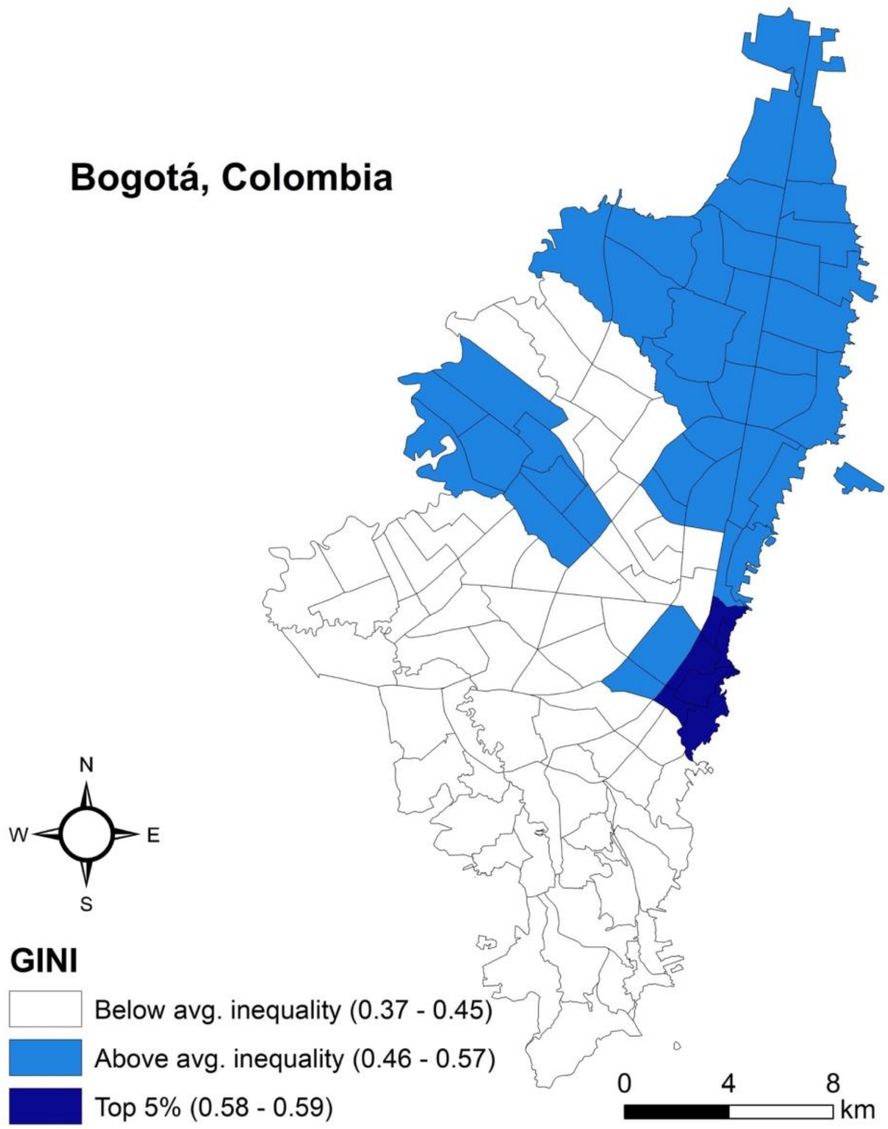
Source: FIP calculations on Colombia's National Police data

The income-inequality variable, as measured by the Gini index, was calculated for each locality[19] in the city of Bogotá. This data were operationalized from Bogotá's 2011 multipurpose survey (Encuesta Multipropósito para Bogotá, 2011) and then georeferenced to each one of Bogotá's 111 neighborhoods. It is important to note that Bogotá's local government does not conduct income inequality surveys on a yearly basis as other countries like the United States do. As a result, 2012 inequality data were not available, instead information on 2011 inequality data were used in this analysis. As seen in Table 3, income inequality data varied across neighborhoods from some relatively moderate levels of inequality, with a Gini coefficient of 0.36, to relatively high levels of inequality with a coefficient of 0.58 in other parts of the city. The locational distribution of this variable across Bogotá's neighborhoods reveals a spatial pattern by which northern communities of the city display higher levels of inequality, while Bogotá's southern neighborhoods present comparatively lower levels of inequality.

As displayed on Figure 3, the highest levels of inequality cluster over Bogotá's central district, predominantly the localities of Santa Fe and Candelaria. Most importantly, higher inequality tends to collocate with the location of higher stratum sections in the city, while lower levels of inequality tend to be present in the southern neighborhoods, where lower stratum dwellings concentrate. Based on spatially comparing the spatial distributions of inequality and stratum, inequality appears to be higher in places where the better-off concentrate, while more impoverished areas tend to be overall more equal.

[19] The city of Bogotá is divided in 19 localities, each of which groups a varying number of neighborhoods. Inequality data are only disaggregated at the locality-level in this geography. As a result, inequality figures for Bogotá's neighborhoods were calculated as an estimate based on the locality-level indicator for inequality.

Figure 3. Gini coefficient per neighborhood in Bogotá during 2011



Source: Encuesta Multipropósito para Bogotá, 2011 (SDP, Boletín #32)

The second independent variable in this analysis was the average neighborhood risk of crime or ANROC. This variable was calculated in two steps: First, an RTM analysis was conducted to identify all micro-level risky places across Bogotá's geography; and second, all micro-level risky places falling directly within each neighborhood were aggregated to create a neighborhood-level measure of criminal risk. Having this objective in mind, an

RTM analysis was conducted to identify the micro-level location of risky places across Bogotá's geography. To build a statistically-valid RTM analysis, the RTMDx software was utilized to model the spatial association between a series of features of the landscape and how these collocate spatially with the location of 2012 violent crime incidents (see Caplan and Kennedy, 2016). To spatially depict the geographic distribution of crime risk through Bogotá's geography, the city was subdivided into a continuous surface GRID of 75 meter-by-75-meter cells (*N*=76,928). The block size was set at 150 meters after assessing Bogotá's average city block size. According to Kennedy et al. (2016), a block size has a practical meaning as it is the most realistic unit the police can use to be deployed.

Table 5. List of potential risk factors

Environmental and Socioeconomic Risk Factors	*N*	Operationalization	Spatial Influence
Banks	1170	Proximity and Density	Up to 450 meters (or up to 3 increments of 150 meters)
Community Kitchens	320	Proximity and Density	
Higher Education Centers	151	Proximity and Density	
Hotels	413	Proximity and Density	
Tourist Areas	2024	Proximity	
Tourist Attractions	306	Proximity and Density	
TransMilenio Stations	145	Proximity and Density	
Drugstores	2526	Proximity and Density	
Medical Clinics	10554	Proximity and Density	
Motor Vehicle Bridges	2834	Proximity	
Pedestrian Only Bridges	2399	Proximity	
Public Hospitals	107	Proximity and Density	
Public Library	20	Proximity and Density	
Schools (Only Private)	1577	Proximity and Density	
Schools (Only Public)	920	Proximity and Density	
Low Strata	1251403	Proximity and Density	
High Strata	423579	Proximity and Density	

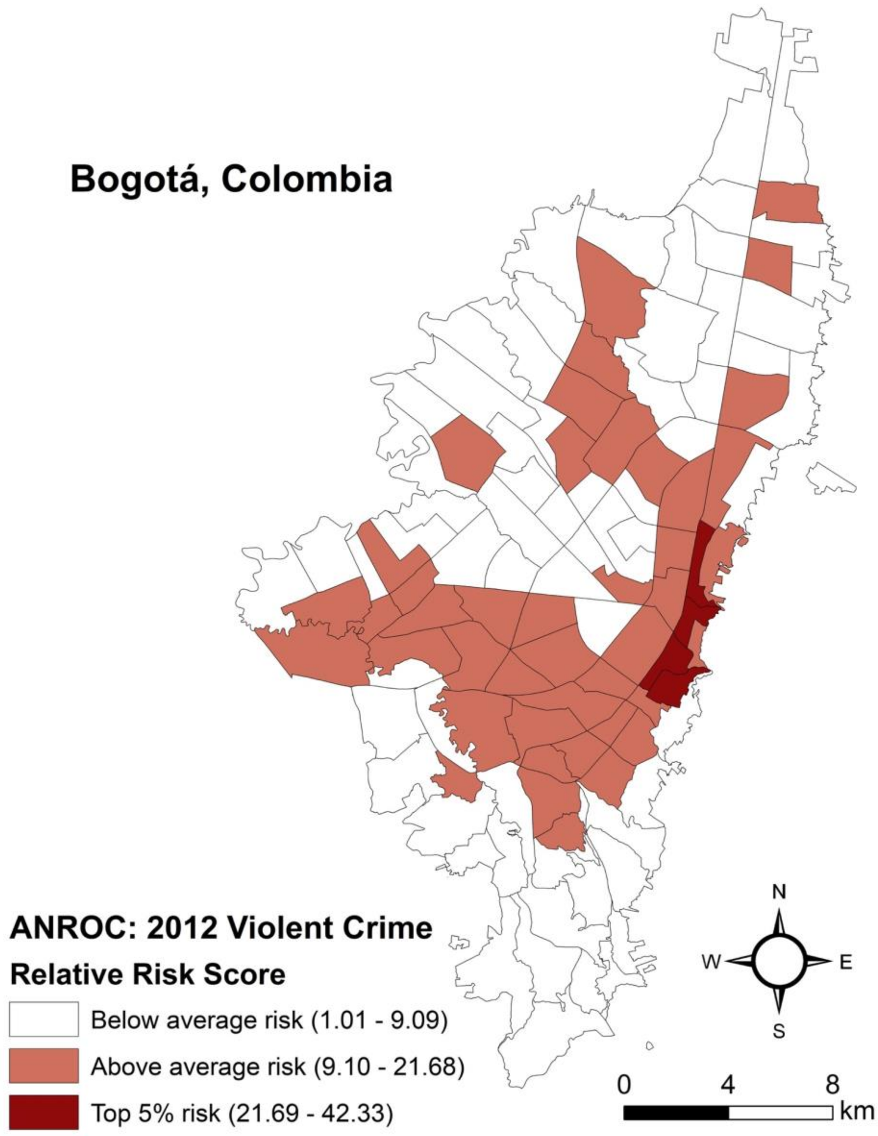
A total of 15 environmental variables and 2 socioeconomic variables were operationalized by their spatial influence, either by their proximity or density, to the location of 2012 violent crime incidents. The selection of these variables and their operationalization within the RTM framework were based on the visual inspection of each variable and their overlap with the location of 2012 violent crime incidents. If a variable appeared (visually) to be concentrating near the location of crime events, this variable's spatial influence was operationalized for "density". However, if proximity (and not density) appeared to explain the overlap with the location of crime incidents, then operationalization by "proximity" was selected. In those scenarios where these differentiations could not be "visually" established, the selection was made for both options. A full list of these environmental factors is presented in Table 5 with details on the number of observations for each variable (*N*), the operationalization parameter used and the spatial influenced applied during the analysis.

As per the results obtained from conducting an RTMDx analysis, a total of 13 risk factors were determined to be statistically significant within Bogotá's RTM model. As a result, 76,928 cells of equal size[20] were created, each of which had a value ranging from 1 (lowest risk / no risk) to 134 (highest risk). In this sense, low stratum units and drugstores were deemed to be the most important predictors for future violent crime incidents, with proximity to these locations presenting a risk of victimization two and three times higher[21] than any other location in the city. These results suggest that the location of these risky features at micro-level places throughout the city of Bogotá is responsible for creating unique contexts of violent crime victimization. In this regard, locations with a

[20] Each cell comprises an area of 5,625 sq. meters (75 m. * 75 m.)
[21] Based on relative risk scores determined for low stratum units (RRV = 2.6) and drugstores (RRV = 1.9).

concentration of “low stratum” dwellings present an increased risk of victimization due to the attracting qualities (e.g., urban decay, unpaved roads, lack of proper public services, etc.) that these micro-level places pose compared to other places across the city of Bogotá.

Figure 4. ANROC measure per neighborhood in Bogotá



An RTM analysis is, on itself, sufficient to determine where, and why, risk exists at certain micro-places; however, the purpose of this analysis was not to assess the micro-level risk of crime in Bogotá but to understand how varying contexts of neighborhood-level crime risk spatially associate with different levels of violent crime incidents. To measure Bogotá's community level risk of crime, ANROC measures were calculated to determine the aggregate-level risk across Bogotá's 111 subdivisions, each of which represents an average of approximately 66,000 people. First, centroids were calculated for each raster cell in the map, and their risk scores averaged to measure the neighborhood-specific risk of crime. As seen in Figure 4, the spatial distribution of neighborhood risk presents a clear geographic pattern by which the central sections of Bogotá are at a higher risk compared to any other areas in the city. As expected, these sections also present elevated levels of inequality and criminal activity.

Results

As per the results of this study, a positive and statistically significant relationship was found between varying contexts of neighborhood crime risk and socioeconomic inequality on 2013 violent crime rates. As seen in Table 6, a total of four OLS regression models were produced to test this relationship by accounting for variations between the separate and combined effect of the two independent variables on 2013 neighborhood violent crime rates.

As noted by Bernasco and Block (2011): "Ill-conditioned data, data characterized by near dependencies between the independent variables, can give rise to collinearity problems whereby the results become unstable under small perturbations of the data" (p. 43). It is therefore essential to include collinearity diagnostics like the variation inflation factors (VIF) analysis to ensure the absence of collinearity problem with the data. In this regard, the current analysis included calculations for the mean and largest VIF values for each multivariate regression model. The highest the VIF value, the higher the chances of multicollinearity with VIF values under 10 generally seen as acceptable (Bernasco & Block, 2011).

First, Model 1 and Model 2 examined the effect that the ANROC measure had on 2013 violent crime rates without including inequality as part of the regression analysis. As expected, ANROC was positively associated with 2013 violent crime rates. Moreover, this model by itself accounts for a significant portion of the variation (24%) in neighborhood rates of violent crime victimization. Similarly, in Model 2, after including a control variable for neighborhood total area, the explained variance remained unchanged at 24%. These results suggest that the inclusion of the total area had no effect on the explanatory power of the ANROC measure in Bogotá's. As seen by the mean and maximum VIF values, the presence of multicollinearity can be ruled out in this analysis.

Table 6. OLS regression models

	Model 1	**Model 2**	**Model 3**	**Model 4**
ANROC	0.798***	0.745***	-	0.626***
Gini	-	-	0.110***	0.091***
Neighborhood Area	-	- 0.09	-	- 0.30
Model Summary				
R^2	0.244	0.253	0.224	0.402
Adjusted R^2	0.237	0.239	0.217	0.386
Mean VIF	-	1.13	-	1.12
Largest VIF	-	1.13	-	1.16
Total # of neighborhoods	111	111	111	111

*** $p < 0.001$

As per the results of Bogotá's RTM analysis, the risk of victimization increased in locations presenting a concentration of low stratum dwellings, proximity to drugstores, and the presence of eleven other risk factors[22]. The combined spatial influences of these physical features create unique contexts for crime to emerge at these micro-level places. As demonstrated, these micro-locations can then be aggregated at the neighborhood-level to estimate the average level of crime risk for entire neighborhoods across the city of Bogotá, thus identifying what physical contexts are associated with an increase in victimization rates. These findings support previous research by Drawve et al. (2016) and Thomas and Drawve (2018) on the use of ANROC to measure the influence that routine activities, the built environment, and the prevalence of criminal opportunities have on violent crime. Furthermore, these results increase support for RTM's ability to accurately identify risk at the neighborhood-level (not just at the micro-level), presenting analysts with a new venue of research in the study of neighborhood effects on crime.

Next, in Model 3 only the measure for neighborhood-level income inequality was tested against 2013 violent crime rates. The analysis found a positive association exists between higher levels of income inequality and varying rates of violent crime victimization in Bogotá. This model was able to explain 22% of the variation in violent crime rates across Bogotá's communities. Therefore, supporting previous research on the pervasive effects that inequality has on violent crime victimization. As argued in Chapter 2 of this study, relative deprivation is a source of social discontent with social order, norms, and values leading to potential eruptions of violence and crime. This result empirically demonstrates

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[22] The following features of the built environment were spatially associated with the risk of violent crime victimization: Banks, medical clinics, hotels, public and private schools, community kitchens, tourist attractions, public hospitals, TransMilenio bus stations, and higher education centers.

how communities with higher levels of inequality are at a higher risk of suffering from higher rates of violent crime.

Lastly, in Model 4, ANROC and Gini measures were included in the same regression model to test the combined effect that criminal risk and inequality have on violent crime outcomes. This model introduced a control variable for neighborhood total area. As expected, the two variables were positively associated with the 2013 violent crime rates while remaining statistically significant. The explained variance increased to 39% of 2013 violent crime rates across Bogotá's neighborhoods. As shown in Model 4, low mean and maximum VIF values indicate the absence of collinearity problems in this model.

This result validates the hypothesis of this study, as the presence of unique contexts of criminal risk and inequality play an important role at explaining the distribution of violent crime victimization rates across Bogotá's neighborhoods. In addition, these results support previous research (see Drawve et al., 2016; Piza et al., 2017; Giménez-Santana et al., 2018) on the benefits of combining the use of social disorganization and environmental criminology theoretical frameworks to further our understanding on the situational dynamics of crime. As noted by Piza et al. (2017), "understanding community-level context may help explain some of the most nuanced research findings" (p. 3001). Thus, the importance of including neighborhood-specific context variables to improve our understanding on the main risk attractors and enablers that lead to expressions of criminal behavior.

Conclusion

These findings are consistent with previous research on the negative effect that relative deprivation (Agnew, 1999; Fajnzylber et al., 2002; Hipp, 2007; Jacobs, 1981; Merton, 1938) has on violent crime victimization. Socioeconomic inequality, whether measured through the spatial distribution of different stratum units or the neighborhood Gini measure of income inequality; present a clear pattern of urban segregation in Bogotá. As argued by Maloutas (2012), "segregation is fed by economic inequality and discrimination and shaped by their filtering through space-related mechanisms and structures, especially, by the shifting and sorting of housing allocation processes" (p. 10). Thus, urban segregation is, in itself, a spatial manifestation of inequality. In this analysis, the link between contexts of inequality and higher rates of violent crime victimization is empirically demonstrated across Bogotá's neighborhoods. A spatial pattern that validates the hypothesis in this study and adds to previous research on the effect that inequality has on crime.

Moreover, these results support the argument that the presence of risky environments across neighborhoods increases the likelihood of victimization. As suggested by Kennedy et al. (2015), "if crime occurred at a place before and if the place is spatially vulnerable, then the likelihood that crime will occur in the future increases" (p. 5). As demonstrated by the results of this analysis, neighborhood crime risk, measured with ANROC and calculated using RTM, explained 24% of the variation in Bogotá's violent crime rates. Therefore, the current study increases support for the ability of the ANROC measure to identify risky environments that are conducive to higher victimization rates.

Finally, the combined influences of unique contexts of socioeconomic inequality and crime risk allowed to explain 39% of the total variation of violent crime rates across Bogotá's neighborhoods. This result validates this study's main hypothesis, given the positive and statistically significant association between the two predictors on the spatial distribution of Bogotá's neighborhood-level violent crime rates. As a result, allowing to improve the general understanding of neighborhood characteristics on crime. Furthermore, this joint model was the most predictive of the four models tested in this analysis. A finding that stresses the importance of jointly analyzing the physical and social correlates of crime to continue advancing in the search of neighborhood effects on crime.

CHAPTER 6: THE CASE FOR CHICAGO, UNITED STATES

"New York is a world city that looks outward: It is not the great American city – that will always be Chicago. To be great is hardly to be flawless, of course. Quite to the contrary and to the dismay of would-be boosters, some of the worst excesses of American life, such as inequality, violence, racial segregation, and corruption, are on major exhibit in Chicago."

- Robert J. Sampson

The city of Chicago has long inspired the works of writers and scholars from an array of different fields. Chicago is home of the renowned Chicago School of urban sociology, best known by the research of scholars such as Ernest Burgess (1886-1966), Robert Park (1864-1944), Clifford Shaw (1895-1957), or Henry McKay (1899-1980), among others. Indeed, the city of Chicago became, in the early twentieth century, the research laboratory for some of the criminology's most influential intellectual movements, drawing attention to the role played by entire communities at explaining the situational persistence of crime (Reiss & Tonry, 1986). For instance, Shaw and McKay pioneered the research regarding the structure and organization of communities in the Institute of Juvenile Research and established the well-known "Chicago Area Project" as their social laboratory. In the 1940s, the so-called ecological approach continued expanding through different studies on neighborhood effects on crime. Soon after, between the 1950s and 1970s, the Chicago tradition switched its focus to the study of individual-level offenders' characteristics, such as the study of crime correlates between criminals and non-criminals (Reiss & Tonry, 1986). In the late 1970s and into the 1980s, the works of Brantingham and

Brantingham (1981) on environmental criminology switched the focus back to places instead of people.

In a recent publication, Sampson (2016) stated, "Chicago is both unique and broadly representative, grounded in a thoroughly documented history and context that helps us understand key patterns" (p. 77). Indeed, it is a city that embodies an array of macro-social characteristics, such as well-defined patterns of localized inequality and high levels of violent crime, all of which make Chicago a suitable candidate to test the hypothesis of the current study. Moreover, the situational dynamics of crime described by the extant literature on violent crime in the city of Chicago suggests that "location matters," and neighborhood social characteristics play an essential role in explaining violence and crime (see Sampson, 2012; Kennedy et al., 2016). Therefore, to continue building on previous research, this study sought to test the relationship between unique contexts of socioeconomic inequality and criminal risk on the varying rates of violent crime across Chicago's neighborhoods.

With this objective in mind and building from previous works on the spatial determinants of crime in Chicago (Park, Burgess & McKenzie, 1925; Shaw & McKay, 1942; Bursik, 1988; Sampson, 2012; Kennedy et al., 2016), this study proposes a novel approach to study the physical and social correlates of violent crime victimization rates across Chicago's communities. This approach consists in jointly studying the effect that socioeconomic inequality and crime risk have on Chicago's neighborhoods violent crime rates. Previous research efforts have focused their attention on neighborhood social characteristics when addressing the situational persistence of crime across Chicago's communities, thus missing to include the influence of the built environment in explaining the distribution of crime across neighborhood environments. For instance, Sampson (2012) analyzed the effect that racial inequality, unemployment rates, and poverty have on crime, when describing the high levels of observed urban segregation in Chicago's communities. According to Sampson's research findings, there is a "synergistic intersection of racial segregation with concentrated disadvantage" (Sampson, 2012, p. 102), thus suggesting that a strong relationship exists between racial segregation and the concentration of social disadvantage in Chicago, not accounting, however, for the effect that the physical environment and the uneven distribution of economic resources have on the spatial distribution of neighborhood-level crime rates.

In order to close this theoretical gap, this study looks at how neighborhoods that present overlapping contexts of socioeconomic inequality and criminal risk suffer from higher rates of violent crime victimization. First, this study analyzes the aggregate spatial influence of the built environment on neighborhood-level rates of violent crime, a major factor in explaining criminal behaviors largely under-studied by ecological theorists (see Shaw & McKay, 1942; Sampson, 2012). With this objective in mind, the current analysis uses the Risk Terrain Modeling (RTM) technique to identify the distribution of spatial vulnerability across Chicago's landscape. However, as previously noted, the existing RTM framework is currently limited to the study of micro-level risk, a level of analysis presently constrained by a lack of social indicators. To overcome this limitation, the current study opted to use the ANROC approach (see Drawve et al., 2016) to identify the distribution of crime risk across Chicago's communities. This novel approach in the study of environmental risk and criminal opportunity at the neighborhood-level effectively allowed to combine the social and physical characteristics of communities to explain the situational persistence of crime and violence across communities in the city of Chicago.

While ecological theorists have focused their attention on the study of an array of neighborhood effects on crime outcomes (see Morenoff et al., 2001; Sampson, 2012), this analysis proposes studying, exclusively, the moderating effect that socioeconomic inequality has on neighborhood violent crime rates. As previously addressed in Chapter 2 of this study, the economic literature on crime supports the pervasive effect that varying contexts of inequality have on violent crime outcomes (see Agnew, 1999; Fajnzylber et al., 2002; Hipp, 2007; Jacobs, 1981; Merton, 1938). However, most studies have analyzed this relationship at higher levels of analysis instead of controlling for neighborhood-level variations (e.g., counties, Standard Metropolitan Statistical Areas, etc.). As a result, the novelty brought by the current study is to analyze, at the neighborhood-level, the relationship between varying contexts of neighborhood inequality and the spatial distribution of violent crime rates. Moreover, as discussed by Stiglitz (2012), the current economic trends brought by the ongoing process of globalization suggest that if nothing changes, inequality rates are expected to continue increasing in the future. Consequently, extreme differences in the allocation of resources can potentially stem an eruption of different expressions of violence and social deviance. This analysis offers new insights into the relationship between neighborhood contexts of socioeconomic inequality and violent crime, thus allowing to better understand the potential consequences of an increase in inequality across communities. In the current study, this relationship was only tested during the year 2013; future studies should analyze this association for additional years to better understand the evolution in the association between contexts of inequality and the likelihood of violent crime victimization.

In sum, the current chapter seeks to address the hypothesis of this study by analyzing how varying contexts of neighborhood-level criminal risks and socioeconomic inequality influence the situational persistence of violent crime rates across Chicago's communities. First, Chicago's neighborhood crime rates are analyzed as the dependent variable of this study, while the average neighborhood risk of crime (ANROC), and neighborhood-level Gini coefficients for income inequality are operationalized as the two independent variables in the analysis. This allows to empirically test the combined effect that varying contexts of environmental risk and socioeconomic disparities have on the spatial distribution of violent crime rates across Chicago's neighborhoods.

Background

To understand the reality of today's violent crime problem in Chicago, one needs to take a step back and look at the history of a city that is deeply stratified along racial lines (Sampson, 2012). Indeed, some researchers refer extensively to Chicago's urban divide across community lines (see Clayton, 1945; Sampson, 2012). As noted by Drake and Clayton (1945), the Black Metropolis is a city within a city, presenting a unique social context like no other, evidencing the intense urban segregation that exists between black and white communities. As the city grew in the early 20th century, foreign-born white communities settled near the industrial zones of transition (mostly zones 1 and 2[23]), occupying small areas sharing the same language and customs. As time passed, new

[23] Based on Burgess (1925) Concentric Zone Model.

generations of “Americanized” immigrants were assimilated by other communities and dispersed through the city (Drake and Clayton, 1945). However, such assimilation never occurred in the case of black communities, staying largely isolated from other communities. Drake and Clayton (1945) found that the “Black Metropolis remained athwart the least desirable residential zones,” (p. 17) therefore indicating that black communities underwent a process of rejection from the general population, effectively insulating entire neighborhoods from the rest of the city.

In fact, by the end of World War I, black communities had become the primary source for unskilled labor and were de facto at the bottom of the social and economic pyramid. This reality contributed to decades of localized violence and crime in predominantly black communities across the city of Chicago. For instance, Drake and Clayton (1945) refer to the increase in crime, drug abuse, and violence by young men lacking opportunities in the inner city of Chicago. They also refer to the negative perception that employers had of young black men, who were largely seen as dangerous individuals. As a result, juveniles' chances of assimilation were further reduced, and their prospects of finding a path out of the vicious circle of crime and violence. Not surprisingly, ecological theorists such as Shaw and McKay focused their research of this particular group on the study of juvenile delinquency, by analyzing how these incidents varied across Chicago’s communities.

Therefore, it is important to revisit from a historical perspective how these changes have had a profound impact on today’s social and economic segregation patterns across Chicago’s communities. As noted by Sampson (2012), “while specific neighborhoods have shifted or traded places, with poverty moving outward from the inner city, the general force of ecological concentration and neighborhood racial stratification continues to have a strong grip on the city" (p. 98). Thus, Sampson suggests that, even today, the city of Chicago continues to be a strongly segregated city.

Park, Burgess, and McKenzie (1925) were among the first scholars to discuss the ecological dynamics of crime and place, using Chicago as their research laboratory. For instance, Burgess based his renowned Concentric Zone Model on his observation of Chicago's community structure, and its subdivision in different economic and cultural groups. In this regard, Burgess (1925) suggested that "the zone of deterioration encircling the central business are always to be found the so-called slums and bad lands with their submerged regions of poverty, degradation, and disease, and their underworlds of crime and vice" (p. 54 – 55), thus referring to the spatial distribution of crime in Chicago and its link to the existence of segregated micro-environments within its urban context. In other words, Burgess hypothesized that social groups could ecologically be depicted by their radial expansion from Chicago's central district outward (Sampson, 2012).

Moreover, they identified the presence of different functioning "natural areas" in Chicago, with entire communities sharing similar physical, social, and cultural characteristics. McKenzie (1925) referred to this reality when noting that "units of communal life may be termed natural areas or formations" (p. 77 – 78). This thus suggests the presence of highly segregated urban areas within the city, each of which appeared to present unique cultural, ethnic, and socioeconomic characteristics bringing people together to these areas. This distribution was not random, but according to Park (1925), responded to an expression of the interaction between human nature and the "metes and bounds" set by the physical environment. Burgess et al. (1925) referred to the concentration of delinquency in Chicago's central district zone, characterized by a lack of cultural controls and high population mobility, while other zones enjoyed lower crime incidents. Thus, it suggests that neighborhood social contexts (e.g., poverty, mobility, inequality, etc.) were associated with the spatial distribution of crime.

Drawing from the works of Park and Burgess, Chicago school sociologists' Shaw and Mckay (1942) suggested a theory of social disorganization to explain the variation of crime across communities in the city of Chicago. Having this objective in mind, Clifford Shaw (1929), together with other scholars (including Harvey McKay) conducted different studies on juvenile delinquency based on the geographic location of these incidents across Chicago's communities. According to Shaw and McKay's observations in the city of Chicago, the existence of "natural areas," explained why the persistence of disorder and delinquency in some areas remained high, despite changes in the social and ethnic characteristics of the people living there. As they argued, "The areas of highest delinquency usually coincide with those sections of the city that manifest a relatively large amount of physical and social deterioration" (p. 424), thus suggesting that the presence of unique contexts were associated with the spatial distribution of crime across Chicago's communities.

Shaw's "situational approach" to the study of delinquency became a novelty at the time, as it eventually allowed to shift the focus from the study of offender's individual characteristics to the study of places. In fact, Shaw became one of the first American sociologists to demonstrate the locational variation of crime incidents in a major city such as the city of Chicago (Sampson, 2012). As previously noted, despite the important contribution of Shaw and McKay's research on Chicago's community-level determinants of juvenile delinquency and disorder, critics have pointed out their inability to account for the effect of the built environment when explaining the spatial distribution of delinquency. As argued by Caplan and Kennedy (2016) "the failure to account for the effects of community characteristics, or environmental features, in attracting illegal behavior and spurring crime is surprising, given their huge effort in identifying spatial patterns of delinquency though mapping incidents" (p.3). Indeed, Shaw and McKay paid little attention to the effect of the built environment at explaining the causes of delinquency, instead treating environmental factors as purely coincidental and geographically adjacent to one another. Other criticisms drawn from their works was the difficulty in replicating their findings outside of Chicago. Bursik (1988) indicated that, "the degree to which findings found in Chicago can be generalized to other cities is unclear" (p. 525 – 526). Therefore, suggesting that other factors (e.g., the spatial influences of the built environment) should be considered when analyzing neighborhood-level criminogenic contexts.

The current analysis suggests studying neighborhood physical and social characteristics as a way to improve the general understanding on the persistence of violent crime victimization rates across communities. Lastly, Shaw and McKay's continued focus on juvenile delinquency in Chicago missed the opportunity to assess the impact of other forms of violent crime. For instance, the current study proposed studying the combined influence of homicide, robbery, and aggravated assault incidents. By jointly analyzing all incidents of violent crime, this study sought to improve the general understanding of the physical and social correlates of violent crime rates across Chicago's communities.

Following the early works of Shaw and McKay, Sampson (2012) presented the "Chicago Project," an ambitious attempt to study how neighborhood-level processes play a key role in explaining individuals' behavior. As Sampson (2012) noted, "Chicago possesses neighborhoods of nearly every ilk – from the seemingly endless bungalow belt of working-class homes to the skyscrapers of the Loop, the diversity and disparities of Chicago are played out against a vast kaleidoscope of contrasts" (p. 76), therefore characterizing the city of Chicago as other scholars have before him, as a city both unique and broadly representative.

The Project on Human Development in Chicago Neighborhoods (PHDCN)[24] became the source for most of the data employed in the so-called "Chicago Project." This project was part of a significant interdisciplinary effort by various scholars (including Robert Sampson) who analyzed the social dynamics in Chicago's neighborhoods. The PHDCN conducted on-site studies across Chicago's communities to improve the general understanding of the central pathways leading to juvenile delinquency, crime, drug abuse, and violence. Sampson's approach to the study of Chicago's neighborhoods is both unique in its approach and innovative in the way he proposed to study community-specific social processes.

In a publication by Morenoff, Sampson, and Raudenbush (2001), homicide rates in Chicago's neighborhoods were linked to the concentration of social disadvantage and low collective efficacy. In their study, Chicago's neighborhoods were measured as 343 neighborhood clusters (NCs) composed of spatially contiguous and socially similar census tracts. According to Morenoff et al. (2001), these neighborhood subdivisions offer a more

[24] https://www.icpsr.umich.edu/icpsrweb/PHDCN/about.jsp

realistic depiction of Chicago's actual community structure as opposed to other studies using "artificial" neighborhood border lines that can miss the ecological properties shaping social interactions. These so-called NCs are representative of relatively homogeneous groupings of people with similar socio-economic, ethnic, and racial backgrounds (Sampson, 2012). Nonetheless, such subdivisions are subject to the arbitrary judgment made by the authors on what conforms a neighborhood and may result in a loss of variation. As such, any approximation to a neighborhood measure will remain an estimation of the spatial reality that constitutes the social interaction of individuals living in close proximity. In the current study, census tracts were operationalized as neighborhoods given the objective nature of this unit of analysis, offering a measure that evenly distributes Chicago's population across its geography[25]. However, future studies could re-interpret these results by using alternative units of analysis as new data becomes available at the neighborhood level.

As per Sampson's conclusions, the concentration of neighborhood disadvantage and collective efficacy are associated with the persistence of crime in some of Chicago's communities. The racial segregation and resource deprivation experienced by predominantly black communities, some of which present patterns of durable segregation even after decades of ethnic change across predominantly white neighborhoods, can help to explain a never-ending cycle of deprivation and racial inequality across Chicago's geography. Moreover, the concentration of neighborhood disadvantage and inequality have enduring effects on violence and crime (Sampson, 2012). Therefore, it suggests that contexts of racial inequality and the concentration of neighborhood disadvantage can

[25] On average each census tracts in Chicago is representative of a population of approximately 3,400 people.

explain the persistence of crime and violence in some of Chicago's communities. As previously noted, Sampson (2012) refers to concentrated inequality in the study of Chicago's communities from a racial perspective. To explain the variation in the neighborhood violent crime rates, this study proposes addressing the various risks emanating from the physical environment, as well as the uneven distribution of resources, to explain the variation of violent crime rates across Chicago's communities.

A more recent study by Kennedy et al. (2016) found that the risk of aggravated assault victimization in the city of Chicago was linked to the situational proximity to problem buildings, followed by gang hot spots and the nearby presence of foreclosures. These results were obtained after conducting a risk terrain modeling (RTM) analysis for all aggravated assaults in 2012 inside Chicago's borders. A total of 23 potential environmental risk factors were tested in the study against the location of the 2012 aggravated assaults (Kennedy et al. 2016). As per the authors' conclusions, the combined effect of statistically significant risk factors in a reduced number of places across Chicago can determine where the vulnerability to future aggravated assaults is higher than anywhere else in the city. Moreover, Kennedy et al. (2016) suggest that "hot spot analysis is enhanced by knowledge of the vulnerable locations in which the high-risk factors prevail" (p. 16), thus suggesting that risk-prone (i.e., vulnerable) locations that overlap with places presenting a concentration of past crimes can offer precise information regarding the location of future crimes.

Data and Research Methods

The City of Chicago is the third largest city in the United States after New York and Los Angeles, with a population of approximately 2.7 million (U.S. Census Bureau, 2010). It expands over an area of approximately 237 sq. miles (City of Chicago Statistics). According to the U.S. Census Bureau (2012), Chicago's city-level inequality measure (Gini = 0.53) was, in 2012, above the U.S. national average (Gini = 0.47), thus suggesting an elevated level of inequality. However, if we take a closer look at this same metric at the neighborhood level, we can find broad disparities within the city of Chicago. For instance, while some neighborhoods in 2012 had a comparatively low level of income inequality with a Gini index of just 0.25, other communities presented very pronounced levels of inequality with a Gini coefficient of 0.72. In other words, inequality varies significantly across Chicago's neighborhoods, suggesting the presence of very different contexts of inequality across the city's geography.

Moreover, in 2012, Chicago experienced a 16% increase in the rate of homicide incidents compared to the previous year, with a total of over 500 homicides over that same year. According to Kennedy et al. (2016), such a spike in violence in Chicago could be attributed to lax gun laws in jurisdictions outside of the city, feuding gang groups, delinquency, and drugs. However, the situation differs when analyzing aggravated assault incidents, which continued to decrease over the year 2012 but remained approximately 150% higher than the rest of the United States. In total, over 12,000 aggravated assault incidents were reported in the city according to Chicago's Police Department statistics. As noted by Kennedy et al. (2016), violent crime continues to be an ongoing problem in the city of Chicago. It is therefore essential to continue extending the literature on the varying physical and social correlates of violent crime to better understand the situational persistence of violent crime across Chicago's communities, particularly at the neighborhood level.

Table 7. Descriptive statistics

	Obs.	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Dependent variable							
2013 Violent Crime Rate	797	7.78	7.66	0	52.14	1.73	6.86
Independent variables							
ANROC	797	22.05	12.72	1	67.11	0.67	2.96
Gini	797	44.94	7.16	24.88	72.15	0.60	3.55
Neighborhood Area (Sq. Miles)	797	0.29	0.41	0.003	8.36	11.29	203.95

Sources: Chicago Police Department (2012; 2013); U.S. Census Bureau (2012).

After inspecting the descriptive statistics seen in Table 7, 2013 neighborhood crime rates were found to have a leptokurtic (6.86) distribution. To induce normality, a square root transformation was conducted on the dependent variable[26]. The transformed 2013 violent crime rate variable ranged from 0 to 7.22 with a mean of 2.48 and a standard deviation of 1.28. Similarly, the control variable to the current analysis, "Neighborhood Area", was found to be highly skewed (11.29) and leptokurtic (203.95). To induce normality on the control variable given its very significant skewness, a log transformation was conducted on these values. As for the two independent variables, the ANROC measure ranged from 1 (no risk) to 67.1 (highest risk), and the Gini measure ranged from 24.8 (lowest inequality) to 72.2 (highest inequality). The two independent variables for this

[26] Different transformation techniques (e.g., natural logarithms, square root, etc.) were tested to induce normality. However, the square root transformation was chosen as the most appropriate method given its less "aggressive" transformation (see Jacobs, 1981).

study did not present normality issues, as their values remained within the acceptable threshold (Gravetter & Wallnau, 2014).

Table 8. Correlation matrix

	2013 Crime Rate	ANROC	Gini	Neighborhood Area
2013 Violent Crime Rates	-	0.42***	0.18***	- 0.02
ANROC		-	0.16***	- 0.52***
Gini			-	- 0.17***
Neighborhood Area				-

*** $p < 0.001$

To test the relationship between the two independent variables and the dependent variable in this study, a correlation matrix was calculated. As seen in Table 8, ANROC and Gini measures were highly correlated with 2013 violent crime rates[27]. As expected, this relationship was positive and statistically significant ($p<0.001$) for both independent variables, indicating a strong association between neighborhood contexts of risk and income inequality with 2013 neighborhood-level violent crime rates. Furthermore, a positive and statistically significant ($p < 0.001$) correlation was observed between the two independent variables, thus suggesting that varying degrees of neighborhood risk and inequality were also correlated. As a final observation on the correlation matrix, both independent variables appeared to be highly correlated with the control variable for neighborhood land area.

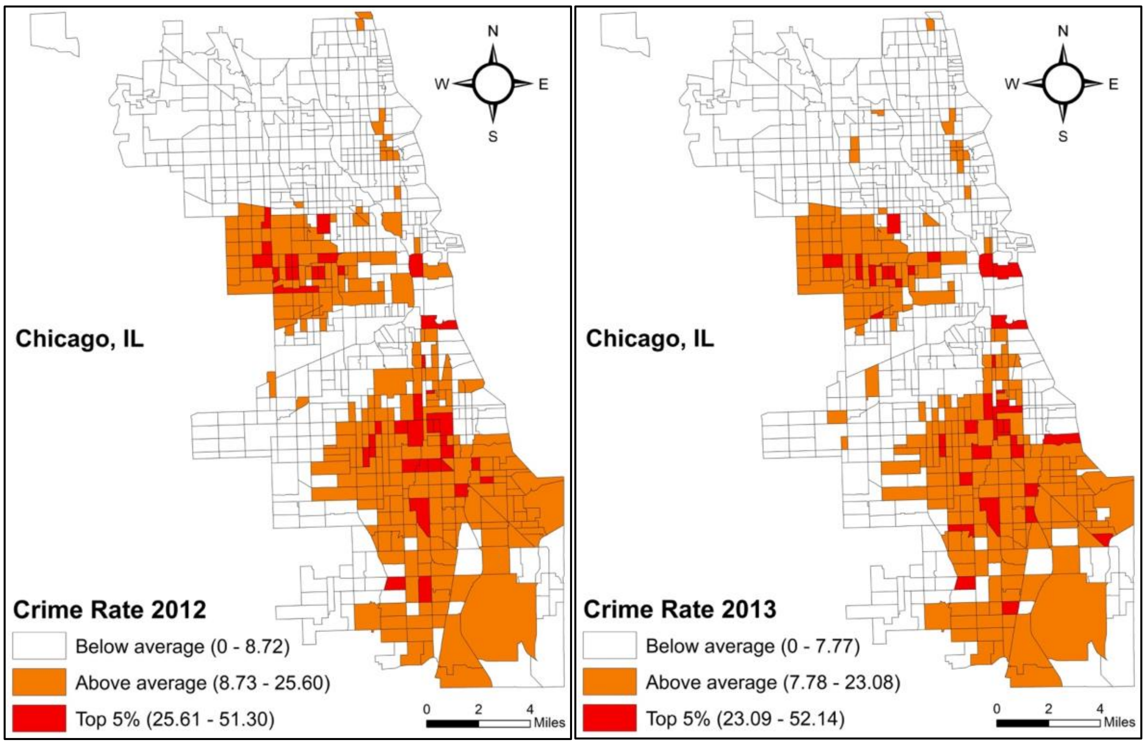
First, the current study measured Chicago's violent crime rates for each neighborhood within the study area. For the purpose of this analysis, U.S. Census Tracts

[27] 2013 transformed measure for neighborhood crime rates.

were operationalized as neighborhood units. The FBI’s Uniform Crime Reporting (UCR) program defines violent crime as “those offenses which involve force or the threat of force.” In the current analysis, three types of violent crimes that occurred in 2012 and 2013 within Chicago's city boundaries were jointly analyzed: homicide, aggravated assault, and robbery. Crime data were directly obtained from Chicago’s City Data Portal, an open-source web site offering detailed crime records from 2001 to the present. It is important to note that all violent crime data were already geocoded at the time of its extraction, with XY attributes available for each crime observation.

A total of 20,064 violent crime events occurred in Chicago during 2012, of which 2.5% (505) were homicide incidents, 67.2% (13,486) were robberies, and 30.3% (6,073) were aggravated assaults. Then, in 2013, violent crime counts totaled 17,684 incidents, of which 2.4% (422) were homicide offenses, 66.8% (11,820) robberies, and 30.8% (5,442) aggravated assault incidents. These figures suggest that overall violent crime outcomes decreased by 12% between the years 2012 and 2013. However, if we analyze the distribution of violent crime incidents by crime type, these figures suggest that, at least proportionately, all three crime types remained constant over time. To calculate neighborhood violent crime rates, the total number of violent crime outcomes were divided by the population of each neighborhood in Chicago; the resulting figures were then multiplied by 1,000 to obtain the final violent crime rate for each neighborhood within the city of Chicago. The current analysis utilized 2013 neighborhood violent crime rates as the dependent variable to measure the effect that unique contexts of criminal risk and inequality had on violent crime rates. As for 2012 violent crime counts, this data were utilized within the RTMDx framework to identify the location of risky places across Chicago's communities.

Figure 5. Comparing neighborhood violent crime rates in Chicago between 2012 and 2013



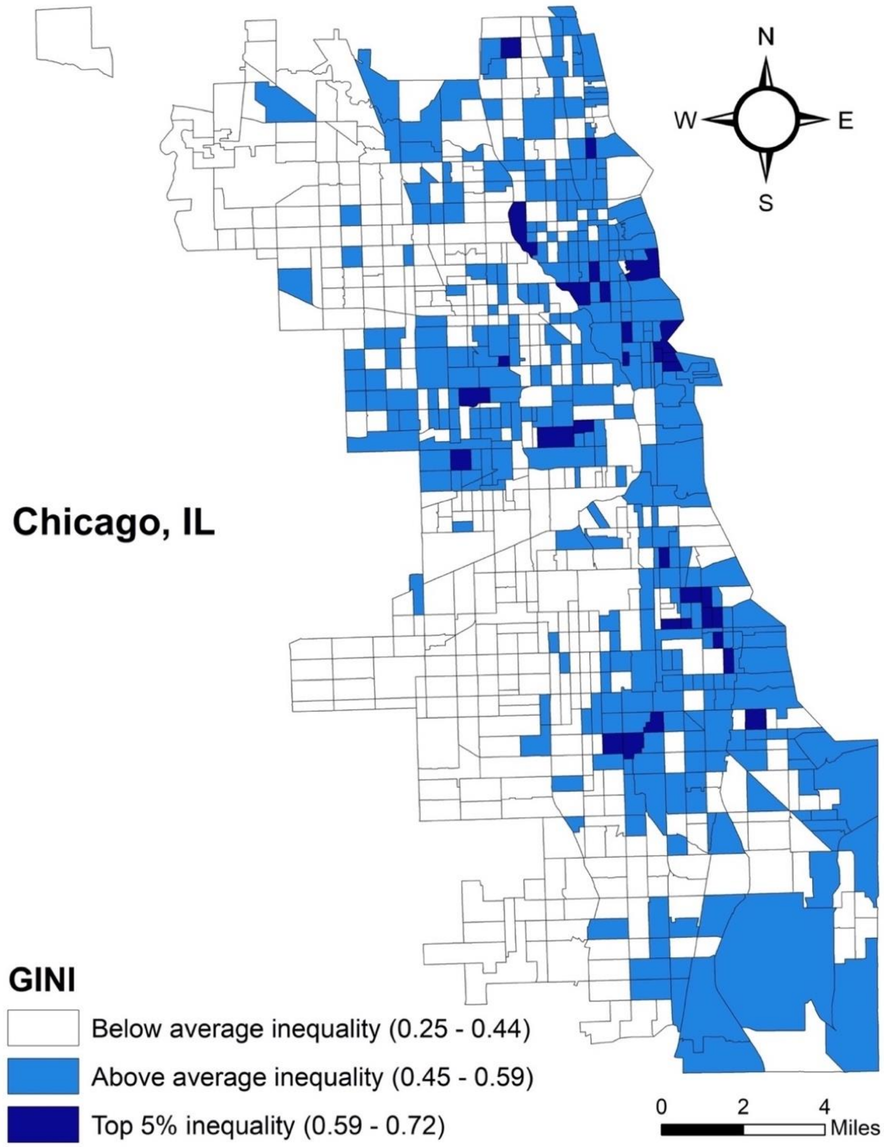
Source: Chicago Police Department

As seen in Figure 5, the spatial distribution of Chicago's neighborhood violent crime rates was concentrated during 2012 and 2013 in the south and central-west parts of the city. This figure illustrates not only the concentration of violent crime in a reduced number of neighborhoods (displayed in red), but also the situational persistence of violent crime over time. Therefore, it supports the extant literature on neighborhood effects on crime and how they can play an important role in attracting crime and violence to a reduced number of communities (Park, et al., 1929; Shaw & McKay, 1942; Bursik, 1988; Sampson, 2012). Moreover, differentiated ecological contexts (i.e., urban segregation, mobility, unemployment, etc.) could contribute to the unequal distribution of violent crime rates across Chicago's neighborhoods. In line with this argument, the current analysis studies how varying contexts of income inequality and criminal risk contribute to an increase in violent crime rates across Chicago's communities.

Then, Gini estimates for each census tract within the city of Chicago were obtained from the U.S. Census Bureau[28]. Specifically, the dataset[29] utilized for this analysis was obtained from the 2012 American Community Survey estimates. All Gini data were spatially joined to Chicago's census tract boundary layer, the reference file for this analysis. As seen in Figure 6, the spatial distribution of inequality across Chicago's neighborhoods presents several well-defined clusters in the south, north-east, and west of the city. This suggests that varying contexts of income inequality exist throughout Chicago's communities. In Figure 6, neighborhoods within the top 5% of income inequality were displayed in dark blue. These locations had the highest levels of inequality, as noted by their GINI index measures ranging from 0.59 to 0.72. According to Stiglitz (2012), places with a GINI index over 0.5 are considered as having elevated levels of inequality.

[28] https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml
[29] Dataset: B19083 for GINI: Index for Income Inequality

Figure 6. Gini index per neighborhood in Chicago during 2012



Source: U.S. Census Bureau (2012)

Next, the average neighborhood risk of crime (ANROC) was calculated as the average relative risk for each neighborhood within the city of Chicago. First, to identify the micro-level location of risky places across Chicago's communities, a risk terrain model (RTM) analysis was conducted utilizing the location of violent crimes in 2012 against a list of potential environmental risk factors (see Table 9). For this purpose, the city of

Chicago was subdivided as a continuous surface GRID of 250-by-250 feet cells (N = 109,571), and analysis increments were set at 500 feet with up to three increments or 1500 feet.

Table 9. List of potential risk factors

Environmental Factors	***N***	**Operationalization**	**Spatial Influence**
Foreclosures	15288	Proximity and Density	
311 Serv. Req. Lights Out	19987	Density	
Gang Hotspots	23061	Proximity	
Problem Buildings	28574	Proximity and Density	
Apartment Complexes	391	Proximity and Density	
Bars	1316	Proximity and Density	
Liquor Stores	926	Proximity and Density	
Night Clubs	128	Proximity and Density	
Gas Stations	139	Proximity and Density	
Gas Stations with Conv. Stores	2834	Proximity and Density	
Homeless Shelters	2399	Proximity and Density	Up to 1500 feet (or up to 3 increments of 500 feet)
Laundromats	173	Proximity and Density	
Bus Stops	10711	Proximity and Density	
ATM Banks	367	Proximity and Density	
311 Serv. Req. Abandoned Vehicles	7137	Proximity and Density	
Grocery Stores	933	Proximity and Density	
Gymnasiums	176	Proximity and Density	
Post Offices	53	Proximity and Density	
Recreation Centers	33	Proximity and Density	
Rental Halls	89	Proximity and Density	
Retail Shops	235	Proximity and Density	
Schools	1021	Proximity and Density	
Variety Stores	124	Proximity and Density	

As previously noted, the presence of crime generators and attractors (CGAs) has a direct influence on crime outcome, as proximity to these spaces create unique contexts for criminal activity. The current analysis tested a number of CGAs, including schools (Roncek & Faggiani, 1985), liquor stores (Block & Block, 1995), recreation centers (Madensen & Eck, 2008), and bars (Ratcliffe, 2012; Roncek & Pravatiner, 1989). A total of 23 potential environmental risk factors were tested using the RTMDx software.

All risk factor data were directly obtained from NIJ's sponsored research study[30] conducted by the Rutgers Center on Public Security (RCPS) in the cities of Chicago, Newark, Kansas City, Glendale, and Colorado Springs. This study's units of analysis comprised all of Chicago's census tracts, operationalized as neighborhoods for the purpose of this analysis. Then, the operationalization of the different risk factor variables was decided after visually inspecting how each risk factor overlapped with 2012 violent crime count locations. For instance, risk factors like problem buildings or apartment complexes were analyzed as a function of their density or proximity to the location of 2012 violent crime events, while known gang hotspots were only operationalized as a function of their proximity.

The resulting Risk Terrain Model (RTM) identified the location of micro-level risky places throughout the city of Chicago. As a result, 109,571 cells of equal size[31] were created, each of which had a value ranging from 1 (lowest risk) to 251.90 (highest risk). As per the results of this RTM analysis, locations within close proximity to foreclosures and problem buildings presented the highest risk of violent crime victimization across the city of Chicago. Based on the relative risk score (RRS) values obtained for the two most significant risk factors (i.e., foreclosures and problem buildings), the risk of victimization more than tripled in places within 1000 feet to foreclosure locations and doubled in locations within 500 ft to places categorized as "problem buildings" across Chicago. Therefore, the spatial influences presented by these physical features create unique behavior settings for crime to emerge at these micro-level locations.

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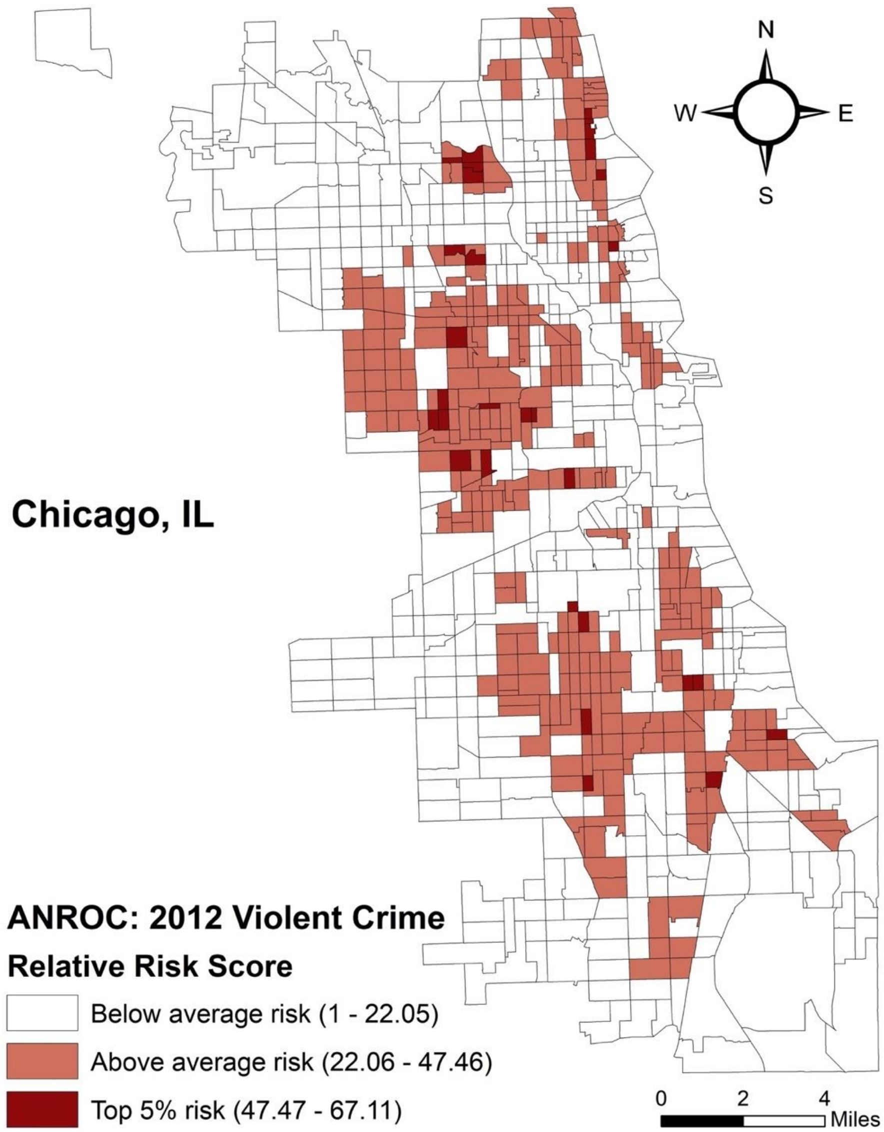
[30] National Institute of Justice Award #2012-IJ-CX-0038: A Multi-Jurisdictional Test of Risk Terrain Modeling and a Place-based Evaluation of Environmental Risk-Based Patrol Deployment Strategies. https://www.nij.gov/topics/law-enforcement/strategies/predictive-policing/Pages/risk-based-patrol.aspx

[31] Each cell comprises an area of 62,500 sq. feet (250 ft. * 250 ft.)

To model the influence of the physical environment at the community level, the ANROC approach was utilized to calculate the average neighborhood risk of crime across Chicago's communities. First, centroids were calculated for each cell in the map and then RTM's RRS values were aggregated at the neighborhood level to obtain the final ANROC measure. As seen in Figure 7, ANROC values ranged from 1 (lowest neighborhood risk) to 67.11 (highest neighborhood risk). The top 5% of riskiest neighborhoods (displayed in dark red) were measured as all neighborhoods with ANROC values of two standard deviations from the mean. These neighborhoods presented the highest risk of violent crime victimization in 2013 based on the presence of unique environmental criminogenic features that attracted violent crime incidents to these communities.

As seen in Chicago's neighborhood map (Figure 7), communities at a higher risk of violent crime victimization were concentrated in the south, central-west and north-east parts of the city of Chicago. Upon visual comparison between Figures 5 and 7, the spatial distribution of neighborhood risk appeared to overlap with some communities presenting during 2013 the highest violent crime rates in the city of Chicago. As noted by Caplan and Kennedy (2016), "risk heterogeneity of environments, as articulated by risk terrain maps, exist prior to the initial victimization and can be enduring" (p. 59). Thus, suggesting that communities presenting a higher risk of violent crime victimization may not, at least initially, present elevated crime levels.

Figure 7. ANROC measure per neighborhood in Chicago



Nonetheless, the presence of environmental criminogenic features makes these neighborhoods more likely to display a high number of violent crime incidents in the future as conditions change. Such variations could respond to changes in social contexts, which can moderate the influence that the built environment has on the likelihood of crime occurrence. In other words, given the presence of favorable social and economic contexts (e.g., low unemployment, income equality, etc.), the relative spatial influence of risky features could be mitigated in these locations, thus explaining why environmental risk may correlate to variations in victimization rates across different community contexts. This relationship will require further study to test the relationship between the moderating effect of favorable social contexts and how this can impact risk-prone locations.

This risk-based approach to the study of violent crime can be used to develop tailored strategies for crime prevention through environmental design (CPTED) to mitigate future crime risks. In other words, if the situational persistence of crime is linked to some features of the built environment, then necessarily, crime reduction strategies have to address how community-specific crime attractors can be transformed to mitigate the risk of future crimes. As discussed by Caplan and Kennedy (2016, p. 13), "RTM articulates a landscape of place-based risks and identifies and helps prioritize evidence-based responses to mitigate risks." Thus, identifying unique contexts of neighborhood-level risk is fundamental to making informed decisions to reduce risk and, ultimately, prevent future crime.

Results

As per the results of the current study, a positive and statistically significant relationship was found between varying contexts of neighborhood-level crime risks and income inequality on 2013 violent crime rates. As presented in Table 10, a total of four OLS regression models[32] were produced to test the separate (Models 1 to 3) and combined

[32] Transformed 2013 neighborhood violent crime rates were utilized as the dependent variable in all three models. This transformation positively strengthened the relationship between the DV and the two IV in this analysis. Alternatively, the log transformation method was tested on the DV, the results did not differ when compared to the current use of the square root technique.

(Model 4) effects that varying contexts of crime risk and inequality have on 2013 neighborhood violent crime rates. To control for collinearity problems between the independent variables, the current analysis included a calculation of variance inflation factors (VIFs) for each regression model.

Table 10. OLS regression models

	Model 1	**Model 2**	**Model 3**	**Model 4**
ANROC	0.042***	0.057***	-	0.055***
Gini	-	-	0.032***	0.025***
Neighborhood Area	-	0.442***	-	0.470***
Model Summary				
R^2	0.179	0.234	0.032	0.253
Adjusted R^2	0.178	0.232	0.031	0.250
Mean VIF	-	1.36	-	1.26
Largest VIF	-	1.36	-	1.38
Total # of neighborhoods (*N*)	797	797	797	797

*** $p < 0.001$

First, Model 1 and Model 2 examined the effect that the ANROC measure for neighborhood risk on 2013 violent crime rates in the city of Chicago. As expected, the association between neighborhood crime risk and 2013 violent crime rates was positive and statistically significant. Moreover, these results indicate that the ANROC measure accounts for 18% of the variation in Chicago's neighborhood violent crime rates. As seen in Model 2, once the control variable for neighborhood area had been added to the regression model, the explanatory power of the ANROC measure increased from 18% of the explained variance to 23%. The mean and maximum VIF are low and indicate the absence of collinearity.

Based on RTM's results for Chicago's analysis, the risk of violent crime victimization in the city of Chicago significantly increased in locations within proximity to foreclosures, problem buildings, and a number of other features from the landscape[33]. These combined physical features create unique contexts for crime to emerge at these micro-level locations. As demonstrated with this analysis, RTM's cell outputs can be aggregated to create a neighborhood-level measure of crime risk, thus supporting previous research by Drawve et al. (2016) and Thomas and Drawve (2018) on the utility of the ANROC measure to explain the variation in violent crime rates. In sum, these results increase support in the ability of RTM, a technique commonly used to study micro-level risky locations, to model how the built environment affects violent crime outcomes at the neighborhood level.

Then, Model 3 analyzed the effect that varying contexts of neighborhood-level inequality had on 2013 violent crime rates across Chicago's communities. According to these results, a positive and statistically significant relationship exists between neighborhood-level inequality and changes in neighborhood violent crime rates, therefore building on the extant literature on the pervasive effects of inequality on violent crime levels. As noted by Jacobs (1981, p.1), "where there are extreme differences in the allocation of resources to individuals, less fortunate men will compare their life chances to others and decide that legitimate avenues to material reward are not sufficient." Thus, comparisons among individuals induced by economic inequality can increase the likelihood of violent crime.

[33] Through the use of RTM, the current study found that the following features of the built environment were spatially associated with the risk of violent crime victimization: Known gang hot spot places, bus stops, variety stores, grocery stores, schools, gas stations, lights out (311 requests for service), liquor stores, ATMs, retail shops, public housing, post offices, and bars.

In the current study, such effect is demonstrated at the neighborhood-level unit of analysis to conclude that varying contexts of income inequality have a direct impact on the observed variation of violent crime rates across communities. If analyzed independently, the inequality measure can only explain 3% of the variation in the rate of violent crime across Chicago's communities. Therefore, inequality can only explain a small, but still significant, portion of the variation of crime figures, suggesting that other social contextual variables should be jointly analyzed with this predictor to better understand the variation of crime rates across Chicago's neighborhoods.

Lastly, Model 4 analyzed the combined effect that varying contexts of neighborhood crime risk and income inequality had on 2013 violent crimes rates while controlling for neighborhood area size. As expected, the results indicate that a positive and statistically significant association exists between the two predictors and the rate of violent crime across Chicago's communities. The explained variance of this joint model increased the observed changes in 2013 violent crime rates across Chicago's neighborhoods to 25%. The mean and largest VIF values are low, which indicates the absence of collinearity between the independent variables in this analysis. These results support the central hypothesis of this study, given that the presence of unique contexts of neighborhood-level inequality and criminal risk produced an observable increase in the rates of violent crime. Moreover, these results support the utility of combining the theoretical frameworks of environmental criminology (i.e., how the immediate environment influences the spatial distribution of crime) and social disorganization (i.e., how inequality weakens social controls). The combination of these two approaches can improve our understanding of the main driving factors influencing the situational persistence of crime at the neighborhood level (see Piza et al., 2016).

As noted by Sampson (1985), neighborhood characteristics (e.g., inequality, mobility, or poverty) can explain the variation in violent crime victimization across communities. However, relying exclusively on social factors and not accounting for the influence of the built environment can limit our understanding of the factors driving criminal behavior (Caplan & Kennedy, 2016). Thus, it is important to identify both the ecological and social factors directly influencing the spatial distribution of violent crime rates across different neighborhoods.

Conclusion

The city of Chicago became, over the last century, the epicenter for some of the most important breakthroughs in criminological research theory. The renowned Chicago School of Urban Sociology used the city of Chicago as their research laboratory. The early works of Park, Burgess, and McKenzie (1925) and Shaw and McKay (1942) defined the contours of urban sociology and revolutionized the study on how community structure and organization have a direct impact on violence and crime. Their works reinforced the importance ecological forces have in explaining the spatial distribution of crime across space. Most importantly, their findings brought new insights on the importance of studying the influence of places, and not people, in generating and attracting criminal behavior. As noted by Sampson (2012), what makes the Chicago school framework still relevant today in the study of neighborhoods is its emphasis on the characteristics of places and not people, its focus on neighborhood-level structural differentiation, and its recognition of significant macro-social forces.

Building on the extant literature on neighborhood effects on crime (Park, Burgess, & Mckenzie, 1925; Shaw & McKay, 1942; Wilson, 1987; Sampson, 2012), the current study analyzed how contexts of inequality and environmental risk associate with the spatial distribution of violent crime rates across Chicago's communities. As per the results of this analysis, the presence of unique contexts of income inequality and criminal risk appeared to explain 25% of the variation in the spatial distribution of violent crime across Chicago's neighborhoods. These findings are particularly relevant to the study of the social and physical determinants of crime at the neighborhood level. Moreover, it reinforces the utility of the ANROC measure as a valid technique in the study of the main physical and social correlates of violent victimization across neighborhoods.

The current study identified the distribution of physical risks across Chicago's communities utilizing RTM. According to Model 4, the ANROC measure combined with inequality explained 25% of the total variation of 2013 violent crime rates across Chicago's neighborhoods. This finding supports previous research (see Drawve et al., 2016; Thomas & Drawve, 2018) on the utility of combining RTM's analytical approach, a technique commonly used to study micro-level risky places, to the study of neighborhood risky environments. The areas of research of environmental criminology and social disorganization tend to be analyzed separately even though their combined application, as demonstrated in this analysis, could improve our understanding of the interaction between the physical environment and differentiated social contexts (e.g., inequality) in explaining the situational persistence of crime. Thus, to further our understanding on the main neighborhood-level attractors of criminal behavior, a combination of physical and social contexts should be taken into account when studying neighborhood characteristics and how these affect the spatial distribution of crime.

Finally, it is important to mention the existing limitations of using macro indicators at the neighborhood-level to measure individual behavior. Such an extrapolation could overlook important micro-level variations and thusly increase the chances of obtaining an incomplete depiction of the underlying characteristics that affect criminal behavior. The current analysis has attempted to combine the strengths of two distinct levels of analysis (e.g., micro and neighborhood levels), but takes into account this unresolved issue by utilizing the ANROC approach. In this sense, future research efforts should seek to analyze additional contextual variables to explain the variance of neighborhood-level violent crime rates in Chicago. The research should also consider examining how neighborhood physical and social contexts affect multiple crime types (e.g., property crimes) and not just violent crimes.

CHAPTER 7: THE CASE OF PARIS, FRANCE

> *"Society itself contains the germs of all the crimes committed. It is the social state, in some measure, which prepares these crimes, and the criminal is merely the instrument which executes them."*
>
> \- Adolphe Quetelet

In the late 1820s, André Michel Guerry (1802–1866) and Adolphe Quetelet (1796–1874) revolutionized the study of criminology and modern sociology with their detailed account on criminal statistics. In fact, they are considered precursors[34] of what a century later became known as the ecological school of crime (see Elmer, 1933). Not surprisingly, Guerry & Quetelet had a profound impact on the later success of the Chicago school of urban ecology (Beirne, 1993). Their early works (Guerry, 1833; Quetelet, 1835) resulted in the recognition of the two French statisticians for their contribution in mapping the spatial distribution of crime across different regions of France. A century later, Stanciu (1968) presented a unique account on the geography of crime and delinquency within Paris' urban context. In his view, the social determinants of crime in Paris could only partially be depicted using statistics on the location of crime incidents; instead, he believed that conducting extensive interviews greatly improved the general understanding on the main social correlates of criminal behavior. In his detailed study on criminality in Paris, Stanciu (1968) drew dozens of maps detailing the location of the offender's residence, including the location of crime incidents and where these were reported across Paris' twenty

[34] Beirne (1993) argued that Quetelet and Guerry anticipated the work of ecological theorists a century later.

arrondissements[35]. He also included an array of tables detailing various offenders' social characteristics (e.g., address, date of birth, profession, nationality, etc.). Ultimately, Stanciu intended to link the location of crime incidents to other social phenomena, thus improving the overall understanding of the main causes of criminal conduct. Nonetheless, his research remained somehow limited to a compilation of large amounts of data in hopes that future researchers would use this data to analyze the social correlates of criminal behavior.

It is worth mentioning the research of Chombart de Lauwe et al. (1952), who is considered to be one of the first scholars to map the spatial distribution of class and inequality in Paris. In fact, Chombart depicted the presence of three differentiated urban groups that divided the city of Paris: The West bourgeois, the working-class in the East, and the functional center on the right side of the Seine River. He focused on the spatial divisions of Paris across social lines, hence suggesting the presence of unique patterns of urban segregation. This phenomenon was more recently studied in detail by Préteceille (2003, 2006, 2012), who argued that the city of Paris does, in fact, present unique contexts of segregation. His observation is based in the mixed nature of Paris' urban structure. Préteceille (2012) referred to these unique contexts of segregation when noting that "Paris is definitely a segregated city, but its segregation is relative, not absolute; segregated groups are more or less mixed residentially, not totally separated" (p. 173). In doing so, he differentiated the reality of Paris' segregation patterns to those observed in other large cities like Chicago or New York City, a set of geographies that presented defined ethno-racial and socio-spatial urban divisions (Préteceille, 2012). Therefore, the city of Paris offers a

[35] The city of Paris is divided into twenty municipal subdivisions known as "arrondissements".

unique opportunity to test how unique contexts of neighborhood-level inequality associate with varying rates of violent crime victimization.

In this third and last case study, France's capital city is analyzed to test the central hypothesis of the current study. In other words, the current study analyzes how varying contexts of a neighborhood-level crime risk and income inequality are associated with the spatial distribution of violent crime rates across neighborhoods in the city of Paris. With this objective in mind, this study seeks to expand the general knowledge on how different community contexts produce a measurable effect on the variation of neighborhood-level crime incident rates. To date, few studies[36] (see Stanciu, 1968; Bauer, 2006) have studied the spatial distribution of crime in Paris. Therefore, to close the existing theoretical gap between the main physical and social correlates of violent crime victimization, the current study analyzes the variations of neighborhood-level violent crime rates between 2012 and 2013 against a set of physical and social neighborhood-level indicators.

The novelty of this empirical study consists in jointly analyzing the effect that varying contexts of neighborhood-level crime risk and socioeconomic inequality present on the spatial distribution of violent crime rates across Paris' neighborhoods. Few studies (see Drawve et al., 2016; Piza et al., 2016; Thomas & Drawve, 2018) have adopted a similar approach. Thomas and Drawve (2018) recently developed an interactive model that analyzes crime as a product of social factors and elements from physical environments. To continue expanding the current literature on the social and physical correlates of violent

[36] The National Observatory on Crime and Criminal Justice Responses (ONDRP), part of the National Institute for Advanced Studies in Security and Justice (INHESJ), publishes every year a report on the variation of criminality in France. These reports include aggregated spatial statistics on changes in crime in Paris' metropolitan area.

crime victimization, this study analyzes the combined effects of crime risks and socioeconomic inequality across Paris' communities.

Background

At the beginning of the 19th century, the failure of French penal strategies to curb crime and delinquency urged the need to find new avenues of research in crime analysis. For instance, Beirne (1993) argued that in Paris, "Robbery was the sole means of support for at least 30,000 Parisians" (p. 69). In fact, crime reports in the city of Paris became at the time a daily routine for citizens witnessing peaks of violence during the winter seasons that, at the time, attained proportions of "panic and terror" (Beirne, 1993), thereby suggesting that Paris' unique social context played a key role in explaining the increase in crime and delinquency rates. This situation led different researchers and practitioners to try to find alternative explanations to the dramatic rise in violence and crime.

Through the statistical movement to crime and penalty started by Guerry de Champneuf[37], the study of crime dramatically changed. In his early works, Guerry divided France into five different regions, each of which had 17 subdivisions. Benjamin (1962) explained how Guerry had available crime data on the number of individuals accused of committing a crime, as well as records for convicted offenders, but preferred the former to the latter as a more realistic depiction of the number of crimes that occurred. These records were then matched for each department in France against different variables (e.g., age, sex, instruction, etc.) (Elmer, 1933). Over a period of six years, he compiled various crime statistics and created maps based on the geographic location of these incidents (Elmer,

[37] Guerry was Director of Criminal Affairs at the French Ministry of Justice (1821-1835).

1933). According to Guerry's findings, the spatial distribution of crimes against person and crimes against property presented varying spatial and temporal patterns.

As Guerry noted[38]:

> "*There is the influence of climate, and there is the influence of seasons, for whereas the crimes against persons are always more numerous in the summer, the crimes against property are more numerous in winter—so of the crimes committed in the south, the crimes against the person are far more numerous than those of against property, while in the north the crimes against property are, in the same proportion, more numerous than those against the person*."

In Guerry's view, crime was a product of social forces, which could be modeled across time and space. Thus, he openly criticized Lombroso (1911), who had previously claimed the notion of the born criminal, instead switching the focus to the various effects of the social environment on criminality (see Beirne, 1993). In fact, Guerry suggested that the social characteristics of entire regions in France had a direct and measurable impact on the situational persistence of different crime types at these locations.

In 1835, Quetelet published his renowned book "Sur l'homme et le développement des ses faultés, ou, essai de physique sociale," translated to English[39] as "A Treatise on Man and the Development of His Faculties." In his research, Quetelet compared a wide range of statistics (e.g., age, climate, seasons, education, professions, etc.) with different crime figures. According to his findings, the "moral and intellectual qualities of men" were associated with the probability of crime events. These works revolutionized the study of crime and space by offering a macro-social perspective of the social correlates of criminal behavior across regions in France. Not surprisingly, the works of Guerry and Quetelet had

[38] See Elmer (1933)

[39] See Quetelet (2013)

important ramifications in the study of the geographic determinants of crime, particularly in the early works of the Chicago ecological school.

It was not until Stanciu (1968) published his study of “La Criminalité à Paris” (Criminality in Paris) that Paris’s first comprehensive study on neighborhood effects on crime saw the light. In his research, Stanciu (1968) collected large amounts of data on convicted offenders held in two large prisons in Paris. This data included extensive surveys carried over 15 years on offenders’ addresses, dates of birth, marital statuses, instructions, and other demographics. To identify the social correlates of crime in Paris, these records were used to produce multiple tables, charts, and maps. Stanciu openly criticized the use of larger units of analysis other than the city block or street segment.

In his view, any unit of analysis larger than the street block could result in spurious findings, given the existence of differentiated socio-economic and behavioral structures in larger environments. As he noted[40] (1968): “The mixing of groups only occurs in the same streets and not even in their entire extent. We have found in one street bordering an îlot a large number of delinquents but in the other street within that same îlot, not a single delinquent” (p. 12). Therefore, he suggested that criminal behavior is a product of the immediate social environment, not necessarily the result of neighborhood contexts. Similarly, the current study proposes measuring crime risk by modeling the spatial influence of a series of environmental criminogenic features at the street-level. These micro-places are aggregated to the neighborhood level to help understand how neighborhood contexts of risk influence the spatial distribution of crime rates across Paris.

[40] Translated from French: “Le brassage des groups ne se fait que dans la même rue et encore pas sur tout son parcours.”

According to Stanciu's (1968) conclusions[41], "If we can make the government, and a part of the public opinion, admit the failure of the penal system and to understand that criminality can't be reduced without radically transforming Paris's urban landscape, then this book won't be in vain" (p. 361). It is, therefore, essential to account for the effect that social forces have as precipitators of criminal conducts. Surprisingly, Stanciu missed, as other ecological theorists did, the opportunity to identify the varying effects that the built environment has on the spatial distribution of crime in Paris (see Kennedy and Caplan, 2012). Instead, he limited his account of criminogenic factors to the presence of different contexts of frustration, anxiety, poverty, or competition. Therefore, he does not account for the spatial influence of the physical environment to explain the presence of varying criminal contexts across Paris' landscape. The current research aims to expand the current literature by exploring the main social and physical correlates of violent crime victimization across neighborhoods in Paris.

In the 1950s, Chombart de Lauwe et al. (1952) mapped the spatial distribution of social groups and socioeconomic status across the city of Paris. Influenced by Burgess' (1925) research in the city of Chicago, they argued that the city of Paris could be depicted in seven ellipses or stars, a slight change from Burgess' concentric circles model. In the center of this distribution is the business district, which encompasses the northwestern parts of the city of Paris, an area that covers the I[st], II[nd], III[rd] and IV[th] arrondissements, as well as the VIII[th], IX[th], and X[th]. According to Chombart et al. (1952), the business district has a characteristic diurnal working population. This zone is followed by the "transition zone"

[41] Translated from French: "Si nous sommes arrivé à ce que l'Administration admette la possibilité de l'échec de la justice pénale et qu'une partie de l'opinion publique se rende compte que la criminalité ne pourra être diminuée que par la transformation radicale de l'urbanisme parisien alors ce livre n'auras pas été inutile."

formed by the Vth, VIth, VIIth and the central parts of the "periferique" arrondissements. These zones are considered to be ethnically and culturally diverse, thus creating unique forms of "acculturation" and socially distinctive urban environments. Then, the residential and industrial zones comprise neighborhoods within the XIIIth, XVth, XVIIIth, and XIXth arrondissements. The final zones are the "dormitory towns" in the Paris banlieue (suburbs), an area falling outside of Paris' "intramuros" region (i.e., the city's 20 arrondissements) and characterized by its low active population. These zones also comprise large housing projects, like for instance, the Palaisseau-Plessis-Robison districts, which present varying degrees of degradation and marginality. The current study did not address the problematic of crime in communities across Paris' periphery; future studies should expand this research approach to understand the physical and social correlates of crime victimization across Paris' "petite couronne" communities.

The technological revolution brought about by access to new technologies and census data in the early 1970s allowed Freyssenet, Regazzola, and Retel (1971) to publish the first systematic study of spatial distribution of socio-professional groups in Paris. According to their findings, Paris' social structure presents a complex reality with an abundance of socially mixed communities. This phenomenon was studied in recent years by Préteceille (2003, 2006, 2012), who has actively researched the problem of urban segregation in Paris. In his early works, he approached this phenomenon by analyzing the spatial distribution of catégories socioprofessionnelles (socio-professional categories)[42] across the city of Paris. As per Préteceille's research findings, middle-class mixed spaces

[42] As Préteceille (2012) argued, using socio-professional groups instead of income or education indicators offers a meaningful way to measure the degree of segregation across community-environments.

are predominant in Paris with the exception of observed self-segregation patterns by the upper-class group.

In France, ethnic statistics are not allowed by law[43], meaning that there are no official statistics on ethno-racial segregation. This phenomenon can only be approached through the collection of qualitative data sources. For instance, Préteceille (2012) created a "dissimilarly index" to spatially identify the clustering of immigrant groups. His findings suggest that levels of segregation have minimally increased in Paris in the past decades. However, specific segregation patterns appear to be significant in the case of immigrant communities with a lower socio-economic status. He compares this characteristic with ethnic segregation patterns across American cities by stating (Préteceille, 2012), "Unlike the US, we do not see in Paris a mosaic of neighborhoods each dominated by one particular ethno-racial group; areas of higher presence of immigrants are areas where most if not all groups of origins mix" (p. 163). Therefore, Préteceille's findings suggest that a majority of neighborhoods in Paris present a residential mix between immigrant communities and French-born ones.

It is worth mentioning that over 20% of all immigrants live in highly segregated neighborhoods, where they represent more than 50% of the total population. These communities at risk are concentrated in the northern parts of the city of Paris, mostly in the banlieues (suburbs). In these problem areas, the combined effect of high levels of socio-economic and ethno-racial segregation, high unemployment, and precariousness appear to create unique contexts of violence and crime (see Préteceille, 2012). Unfortunately, the current study could not obtain crime data for these neighborhoods located directly across

[43] https://www.insee.fr/fr/information/2108548

Paris' suburbs. Future research should incorporate these sections from Paris' "petite couronne" (Paris metropolitan area) to expand this study's result findings.

Therefore, based on the literature (see Freyssenet et al., 1971; Préteceille, 2003, 2006, 2012), we can assume that Paris presents unique contexts of relative segregation as opposed to absolute segregation, a duality of neighborhood structures that appear to be the dominant environmental setting across the city's landscape. The current study approaches the social reality of socio-economic segregation in Paris through the lenses of the unequal distribution of economic resources across its communities. This allowed us to understand not only the spatial distribution of unique contexts of inequality in Paris but also how these contexts collocate with an increase in the rates of violent crime victimization, thus expanding the current literature on neighborhood-level social and physical correlates of violent crime victimization in Paris.

Data and Research Methods

Paris[44] has a population of approximately 2.2 million[45] people and comprises an area of 105.4 square kilometers (approx. 65.5 square miles). As previously mentioned, it is a city that presents elevated levels of socio-economic segregation across its urban landscape. It is a pattern of segregation that, according to Préteceille (2012), is relative and not absolute, with most communities presenting mixed urban environments. This social reality contrasts with that of other large cities like Chicago where ethno-racial urban segregation is predominant (see Drake and Clayton, 1945). According to Paris' Gini

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[44] Also known as Paris "intramuros" or France's 75th Department.
[45] INSEE (2014). https://www.insee.fr/fr/statistiques/1405599?geo=DEP-75

estimates, overall, Paris had an elevated level of inequality with a Gini index of 0.5 in 2012, while neighborhood-level income inequality coefficients ranged from 0.27 to 0.68[46], thus suggesting a wide variation of inequality patterns across Paris' urban landscape with some neighborhoods presenting very low inequality contexts and others displaying elevated rates of inequality.

In this chapter, an additional neighborhood-level contextual variable for community-level unemployment rates was included as part of the current analysis. Previous studies have addressed the relationship between unemployment and crime rates (see Chiricos, 1987; Raphael & Winter-Ebmer, 2001; Fougère et al., 2009), suggesting a positive association between varying levels of unemployment and crime. The current analysis seeks to expand previous research by analyzing the combined effect that neighborhood-level unemployment has on the varying rates of neighborhood-level violent crime in the city of Paris. This new independent variable is then combined with the two main predictors in this study (i.e., criminal risk and inequality) to analyze how varying neighborhood contexts are associated with community-level violent crime rates across Paris's landscape.

Based on the descriptive statistics for Paris' data (see Table 11), the measure for 2013 neighborhood crime rates was found to be highly skewed (4.60) and leptokurtic (33.40). Similarly, the unemployment rate measure was determined to be leptokurtic (5.79). To induce normality, both variables were transformed using the square-root transformation method. As a result, the transformed 2013 crime rate variable ranged from 0 to 3.97, with a mean of 0.72 and a standard deviation of 0.68. Then, the unemployment

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[46] INSEE (2011, 2012). City-level Gini and values for all IRIS units (*n*= 839) within the city of Paris. Insee-DGFiP Revenus fiscaux localisés des ménages. https://www.insee.fr/fr/statistiques/1893301

rate measure ranged from 1.94 to 5.56, with a standard deviation of 0.53. As for the control variable of this analysis, Paris' neighborhood areas were log-transformed due to the high level of skewness (5.63) on this measure. Regarding the two main predictors (ANROC and Gini measures), the values for ANROC ranged from 1.44 (lowest neighborhood risk) to 21.76 (highest neighborhood risk), and Gini measures ranged from 0.27 (lowest neighborhood inequality) to 0.68 (highest neighborhood inequality).

Table 11. Descriptive statistics

	Obs.	**Mean**	**Std. Dev.**	**Min**	**Max**	**Skewness**	**Kurtosis**
Dependent variable							
2013 Neighborhood Crime Rate	839	0.98	1.66	0	15.78	4.60	33.40
Independent variables							
ANROC	839	7.93	3.55	1.44	21.76	0.91	3.99
Gini	839	43.71	6.45	26.74	67.91	1.03	4.09
Unemployment Rate	839	11.69	3.79	3.76	30.86	1.36	5.79
Neighborhood Area (Sq. Km.)	839	0.08	0.07	0.02	0.89	5.63	50.21

Sources: DSPAP (2012; 2013); INSEE - IRIS (2011; 2012)

For the purpose of this analysis, IRIS statistical divisions[47] were operationalized as neighborhood units of analysis. In France in 1999, the National Institute of Statistics and Economic Studies (INSEE) introduced the "IRIS" statistical divisions dividing the geography of France into small units of statistical information, each of which is composed by a population of roughly 2,000 people. Previous research by Préteceille (2003, 2006) proposed analyzing neighborhood variations by using IRIS units to study spatial

[47] Aggregated units for statistical information (Translated from French, Îlots Regroupés pour l'Information Statistique). https://www.insee.fr/en/metadonnees/definition/c1523

segregation patterns across Paris' greater metropolitan area[48]. Aiming at expanding previous studies on Paris' neighborhood effects, the current analysis used all available[49] IRIS statistical divisions within the city of Paris to study the neighborhood variations in criminal risk and inequality across the city of Paris.

First, neighborhood-level violent crime rates were calculated for each neighborhood within the city of Paris for calendar years 2012 and 2013. All crime records were facilitated by the National Observatory on Crime and Criminal Justice (ONDRP) on data from Paris' Police Prefecture (DSPAP). These data were then geocoded to street-level addresses[50] and incorporated into the analysis.

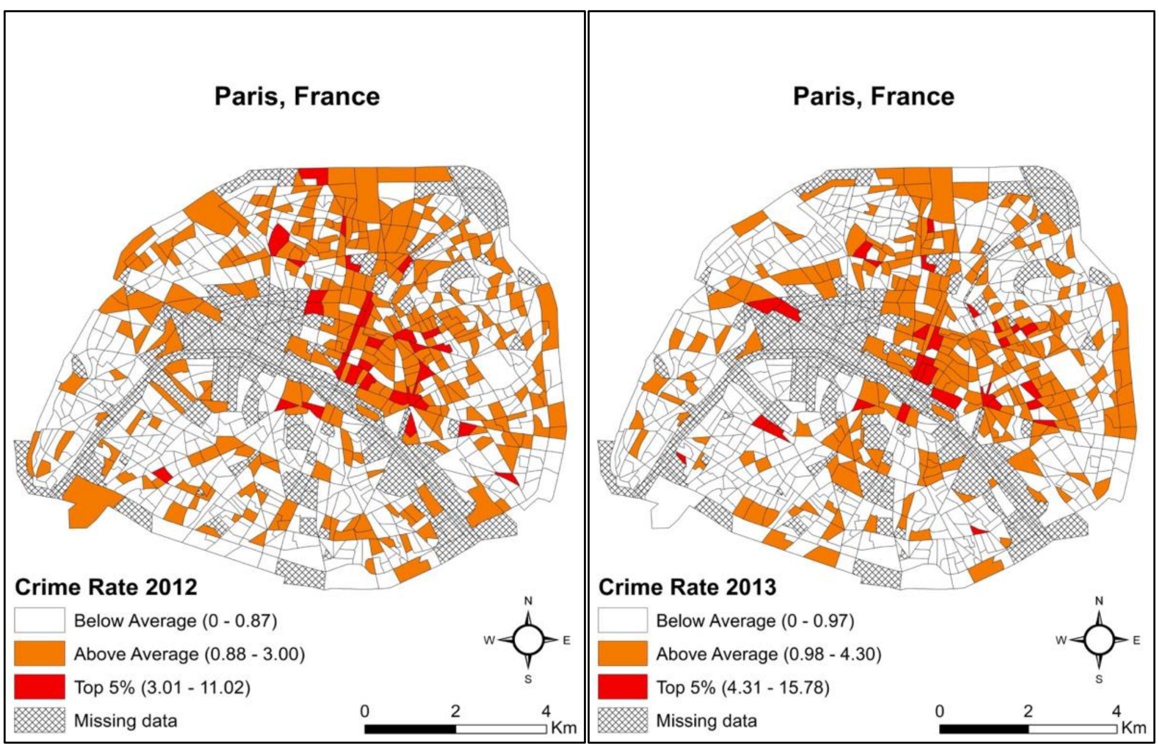
In France, violent crimes are dichotomized in two large categories: economically-motivated crimes ("violences physiques crapuleuse") and non-economically motivated crimes ("violences physiques non crapuleuses") also referred to as "free violence" by the French media[51] ("*violences gratuites*"). For example, revenge-motivated homicides or child maltreatment are considered "violences non-crapuleuses", while financially motivated murders or robberies fall within the second category for "violences crapuleuses"[52].

During 2013, approximately 64.4% of all violent crimes that occurred in Paris were considered to be economically motivated while 35.6% were classified as non-economically

[48] The Greater Paris Metropolis covers the city of Paris and its surrounding suburbs (*banlieue*
[49] The city of Paris is divided in 987 IRIS units, however just 839 statistical divisions had available contextual data for Gini. As a result, all neighborhood units missing inequality data were removed from this study.
[50] The geocoding process was carried out by the National Observatory on Crime and Criminal Justice (ONDRP) in Paris. Crime data was geocoded using NAVTEQ's address locator system.
[51] http://www.lefigaro.fr/actualite-france/2018/02/13/01016-20180213ARTFIG00285-la-hausse-inquietante-des-violences-gratuites-en-france.php
[52] 2016th Annual INHESJ/ONDRP Report: https://inhesj.fr/sites/default/files/fichiers_site/communication/2016_ra_cd_paris.pdf

motivated (INHESJ/ONDRP, 2014). As noted by the same report, the city of Paris had 41% of all economically motivated violent crime in 2013, the largest share in Paris' metropolitan area. However, in the Saint-Denis department (Paris' outskirts), the rate of economically motivated violent crimes emerged as the largest that year with 8.7 crimes per 1,000 people compared to Paris' rate of 7.7 incidents per 1,000 inhabitants (INHESJ/ONDRP, 2014). Therefore, Paris concentrates the largest number of economically motivated acts of violence in its metropolitan area but only the second-largest rate after Seine-Saint-Dennis' department, thus suggesting that the city of Paris, particularly its northeastern peripheral sectors, present unique contexts for economic crime outcomes.

Figure 8. Comparing neighborhood violent crime rates in Paris between 2012 and 2013



The current study utilized all geocoded data for financially-motivated violent crimes ("violences physique crapuleuses"), including violent robberies ("vols avec violence") and homicide incidents[53]. In regard to neighborhood-level population, data were obtained from INSEE's data repositories for each IRIS division within the city of Paris. To calculate neighborhood violent crime rates, the total violent crime count for each community was divided by the total population for each geographic division, and the results were then multiplied by 1,000 to obtain the final measure. As depicted by Figure 8, neighborhood violent crime rates ranged from 0 (none) to 11.2 incidents per 1,000 people in the year 2012, and from 0 (none) to 15.78 incidents per 1,000 people in 2013. A clustering of violent crime incidents can be observed in the city center, specifically in the axis of Saint Denis Street with the Halles' forum. Then, in the eastern sectors, a similar pattern emerges in the Bastille and in the northwestern sectors of Barbes, Pigalle, and between Clichy and La Fourche.

Table 12. Correlation matrix

	2013 Crime Rate	ANROC	Gini	Unemployment Rate	Neighborhood Area
2013 Crime Rate	-	0.31***	0.11**	0.12***	0.11**
ANROC		-	- 0.04	- 0.05	- 0.38***
Gini			-	- 0.17***	0.20***
Unemployment Rate				-	- 0.02
Neighborhood Area					-

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

[53] Homicide incidents were not distinguished between economically motivated and non-economically motivated incidents.

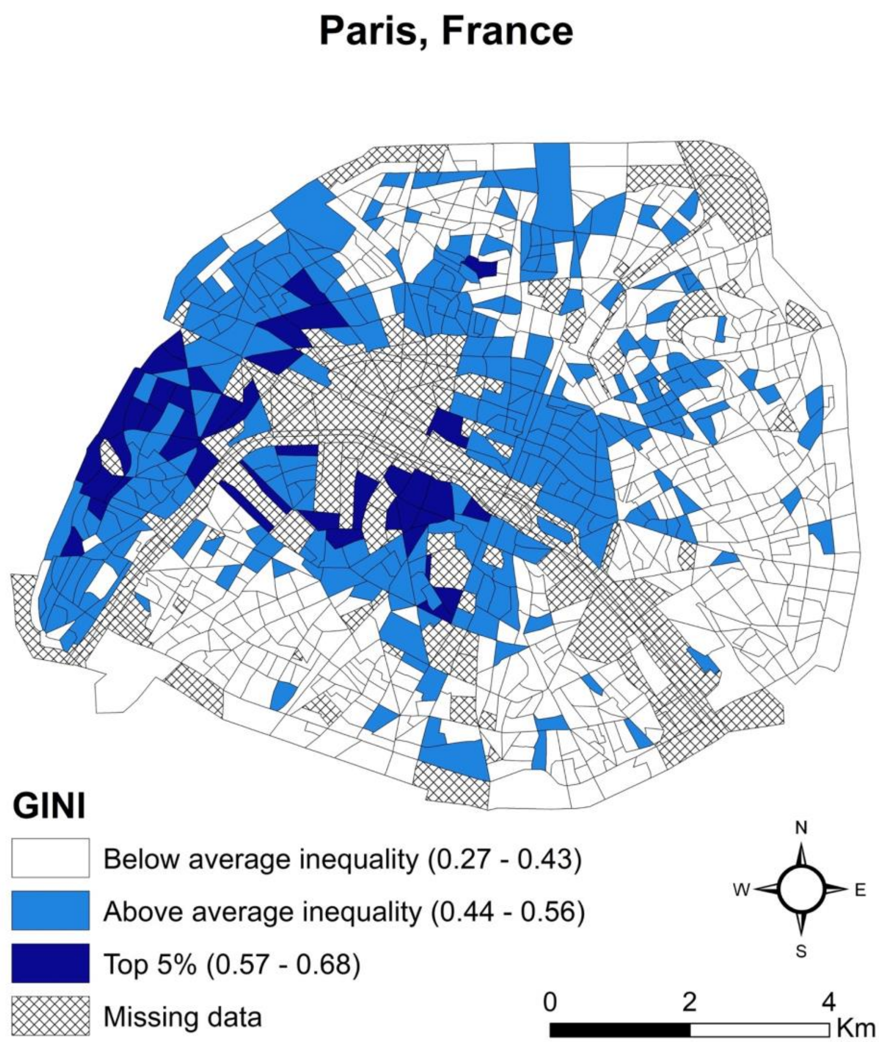
As seen in Table 12, a correlation matrix was built to determine the association between the different variables utilized in the current analysis. As expected, all independent variables were correlated with 2013 neighborhood violent crime rates. It is worth mentioning that the ANROC measure for environmental crime risk appears to have the strongest correlation with this current study's dependent variable. Moreover, neighborhood inequality (Gini) appeared to be positively correlated with 2013 violent crime rates. These results suggest that varying neighborhood contexts of criminal risk and inequality were positively correlated with an increase in violent crime victimization rates. These data increase support for the main hypothesis of this study given the positive correlation between neighborhood-level contexts of crime risk and income inequality on violent crime rates. Additionally, the current analysis includes neighborhood-level unemployment rates as an additional contextual variable. As per the results in Table 12, a positive correlation suggests that the unemployment measure correlates with an increase in victimization rates.

All Gini data records for this analysis were spatially joined to Paris' IRIS boundary reference layer. As seen in Figure 9, the spatial distribution of socio-economic inequality was depicted across Paris' neighborhoods and symbolized according to the relative level of neighborhood inequality. All data records were directly obtained from INSEE's data repository[54] to illustrate the varying levels of socioeconomic inequality across Paris' communities. Neighborhoods missing inequality data were adequately symbolized in the legend and excluded from the analysis; communities at the top 5% of income inequality

[54] Insee-DGFiP Revenus fiscaux localisés des ménages. https://www.insee.fr/fr/statistiques/1893301

were displayed in dark blue while above-average inequality communities were depicted in light blue.

Figure 9. Gini index per neighborhood in Paris during 2012



<u>Source</u>: INSEE-DGFiP IRIS (2012)

Upon visual inspection of the distribution of this measure, a clear spatial pattern emerged in Figure 9 with western neighborhoods in the north of the Seine River and Paris' central areas displaying the highest inequality levels in the city. These sectors are known to concentrate Paris' most affluent neighborhoods (see Chombart de Lauwe et al., 1952). In fact, this distribution supports Préteceille's (2012) observation in regard to the presence of higher patterns of segregation among Paris' upper classes. This development suggests the overlap of contexts of inequality with the location of groups with higher socioeconomic status (SES). Overall, inequality measures were similar to those seen in the previous analyses for Chicago or Bogotá, with Gini coefficients ranging from 0.27 for the least unequal neighborhoods to 0.68 for the most unequal divisions.

The second independent variable of this analysis measured the varying levels of environmental risk per IRIS division in the city of Paris. To assess how environments (i.e., neighborhoods) at risk influence the likelihood of future crime events, it is fundamental first to understand the effect of the built environment in the immediate surroundings of crime events. Making this realization requires one to measure the effect of micro-crime places to understand the dynamics of crime and place (see Groff, Weisburd, & Yang, 2010). Such is an observation also shared by Stanciu (1968) who through his works on the geography of crime in Paris proposed studying the immediate environment (e.g., street-level) as the most appropriate unit of analysis to assess the emergence of criminal behaviors.

With this objective in mind, the Risk Terrain Modeling (RTM) technique was utilized to assess the spatial influences of a series of physical features, and how these features influence the risk of violent crime victimization in the city of Paris. As previously noted in the cases for Bogotá and Chicago, the presence of crime generators and attractors (CGAs) can contribute to creating criminogenic environments (see Bernasco & Block, 2011). Examples of CGAs included in the current analysis for Paris are schools (Roncek & Faggiani, 1985), bars (Ratcliffe, 2012), hotels (Lebeau, 2011), parks (Groff & McCord, 2012), metro stations (Irvin-Erickson & La Vigne, 2015), and bus stops (Hart & Miethe, 2014). Each of these locations can contribute in increasing the likelihood of crime incidents in certain places.

Table 13. List of potential risk factors

Environmental Factors	***N***	**Operationalization**	**Spatial Influence**
Grocery stores	1260	Proximity and Density	
Bars and Nightlife	4448	Proximity and Density	
Low-cost Cafes (Café à 1 Euro)	178	Proximity and Density	
Car-sharing stations	113	Proximity	
Shops and Malls	36	Proximity	
Coffee Shops	3443	Proximity and Density	
Banks	2712	Proximity and Density	
Terrace / Outside seating areas / Stands	20893	Proximity and Density	
Fast food restaurants	113	Proximity and Density	
Gas Stations	144	Proximity and Density	
Post Office	210	Proximity	Up to 450 meters (or up to 3 increments of 150 meters)
Public Housing	2891	Proximity and Density	
Movie Theaters	86	Proximity and Density	
Parks and Public Gardens	511	Proximity and Density	
Pharmacies	1037	Proximity and Density	
Coin-operated public toilets (Sanisette)	395	Proximity	
Schools	1593	Proximity and Density	
Metro Stations	246	Proximity and Density	
Train Stations (RER and SNCF)	72	Proximity and Density	
Taxi Stations	120	Proximity	
Tourist Areas[55]	12	Proximity and Density	
Museum	37	Proximity and Density	
Bike-sharing Stations (Vélib)	68	Proximity and Density	

As seen in Table 13, a total of 23 potential risk factors were tested using the RTMDx software against the location of 2012 violent crime incidents across Paris. All environmental factors were operationalized based on their spatial influence by proximity

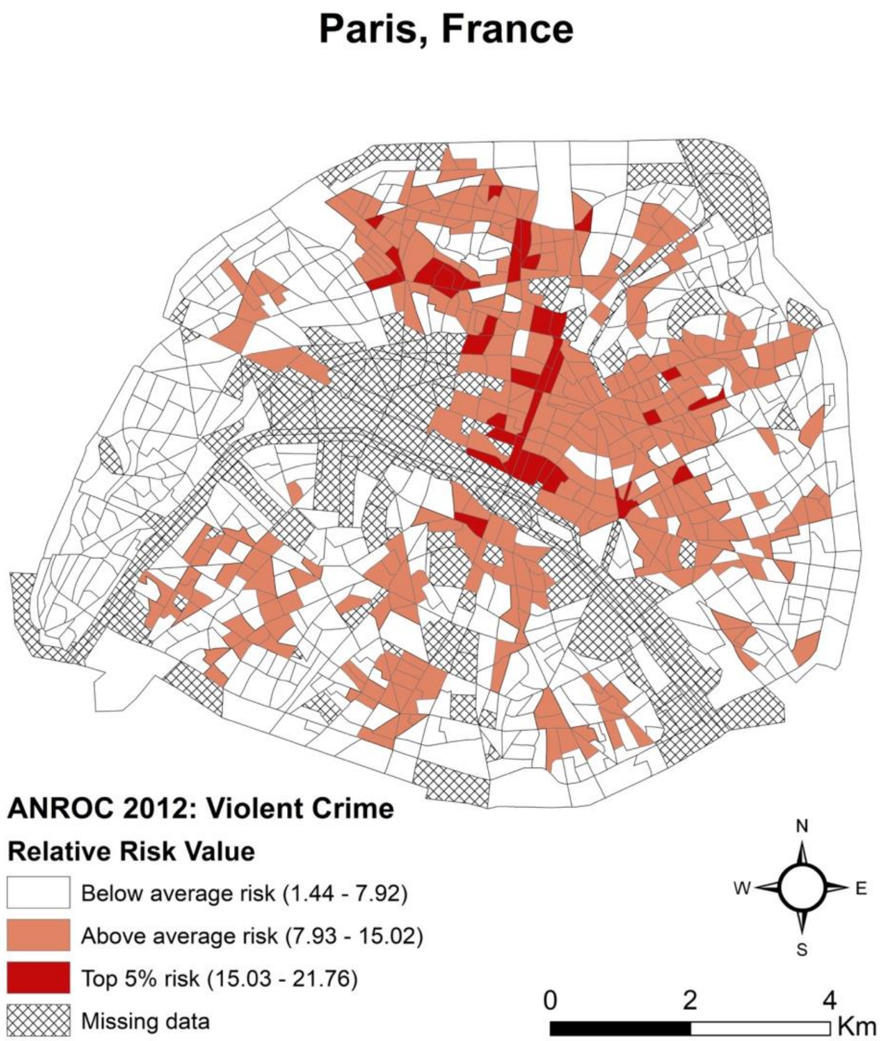
[55] Tourist areas were represented by 12 polygon-features of varying sizes.

or density with a radius of search that ranged from 150 meters to 450 meters (in increments of 150 meters). For instance, car-sharing stations and post offices locations were only operationalized as a function of their distance to the location of 2012 violent crime events; grocery stores and nightclubs were operationalized as a function of density or distance to the location of crime incidents.

To model the spatial influences of all potential risk factors, the city was divided into a continuous surface GRID of 75 meter-by-75-meter cells (*N*=15,772). As a result, the final RTMDx output found an RTM with a total of 11 statistically-significant risk factors associated with the location of 2012 violent crime events. These risk factors included (ranked on the basis of their Relative Risk Value—RRV): Terraces (bars/clubs) and open-air stands[56], fast food restaurants, coin-operated public restrooms, pharmacies, grocery stores, low-cost cafes, schools, bars, public housing, metro stations, and post offices. The presence of these physical features creates unique spatial contexts that lead to varying expressions of deviant behavior. In this sense, locations within 150 meters of a bar terrace location in Paris presents a higher risk of victimization than any other places across the city of Paris. These risky locations offer an opportunity for offenders looking for potential victims that walk to or from these open space areas where people socialize. Similarly, places displaying a concentration of fast food restaurants were at a higher risk of violent crime victimization than other places not presenting these attracting qualities. Therefore, at the micro level, these locations create unique contexts for victimization due to the presence of these environmental features across the city's landscape.

[56] In Paris, retail businesses and bars/clubs require of a city permit to install terraces or stands/window displays. (https://www.paris.fr/professionnels/l-entreprise-au-quotidien/terrasses-et-etalages-3516)

Figure 10. ANROC measure per neighborhood in Paris



To measure neighborhood level crime risk, the ANROC (see Drawve et al., 2016; Thomas & Drawve, 2018) measure was calculated utilizing RTM cell's centroids across Paris' study area. At the time of this calculation, each cell had a value ranging from 1 (lowest risk) to 39.4 (highest risk). In the next step, all centroids were averaged to obtain the ANROC measure for each neighborhood unit in Paris (*N*=839), with ANROC values ranging from 1.44 (lowest risk) to 21.76 (highest risk). As seen in Figure 10, a clear geographic pattern emerged from the spatial distribution of the ANROC measures across Paris' neighborhoods, with a concentration of risky environments within the first four *arrondissements*, as well as parts of Xth and IXth. The second observation from this depiction of crime risk across Paris' neighborhoods is the consistent concentration of risk in the north sections of the Seine river, with the exception of the river's west side. Conversely, these neighborhoods on the west side of Paris presented the highest levels of inequality in 2012 (see Figure 9). This visual comparison explains the non-significant correlation between the two independent variables of the current analysis.

Lastly, a control variable was included for Paris' neighborhoods' total area. As previously discussed in the case studies for Bogotá and Chicago, the measure for neighborhoods' total area varies considerably across jurisdictions. In Paris, smaller communities extend over an area of just 0.02 sq. km while larger neighborhoods can extend over 0.89 sq. km. Given the extrapolation problem of averaging micro-level units of analysis (i.e., RTM's cells) to the neighborhood level and limiting the chance of data inaccuracy, a control variable for neighborhood area size was added to the current analysis.

Results

As per the results of the present study, a positive and statistically significant relationship was found between varying contexts of crime risk and socio-economic inequality on neighborhood-level violent crime rates in the city of Paris. A total of five OLS regression analyses were performed to test the association between the current study's independent variables (i.e., crime risk and inequality) with 2013 neighborhood-level violent crime rates. Moreover, a collinearity diagnostic was included as part of this analysis by using the variation inflation factor (VIF) to test for multicollinearity problems with these data. For each multivariate regression model (see Table 14), the mean and maximum VIF values were reported.

In Models 1 and 2, the relationship between ANROC's measure and the 2013 neighborhood violent crime rates were tested. As expected, the association between contexts of crime risk and neighborhood rates of violent crime was positive and statistically significant. Once the control variable for neighborhood area size was included in Model 2, the explanatory power of the ANROC measure improved from 10% of explained variance to 16%. As seen in Table 14, the VIF values for Model 2 are well below the limits commonly deemed acceptable (see Bernasco & Block, 2011), thus indicating the absence of collinearity issues with these data.

According to RTM's results for Paris' analysis, the risk of violent crime victimization increased in locations within proximity to public terraces, or a concentration of fast food restaurants, as well as other physical features[57]. These combined physical environments create unique contexts for crime to emerge at these micro-level locations, which in turn contribute to an increase in the overall neighborhood risk of crime. These results provide strong empirical support for the predictive capacity of RTM (see Kennedy & Caplan, 2013; Caplan & Kennedy, 2016) while reinforcing support on previous research by Drawve et al. (2016) and Thomas and Drawve (2018) on the use of the ANROC measure to advance the study of neighborhood crime dynamics.

[57] In the current analysis, the following physical features were spatially associated with an increased risk of violent crime victimization: coin-operated public lavatories, pharmacies, grocery stores, low-cost cafés, schools, bars and clubs, public housing, metro stations, and post offices.

Table 14. OLS regression models

	Model 1	Model 2	Model 3	Model 4	Model 5
ANROC	0.059***	0.079***	-	0.078***	0.077***
Gini	-	-	0.012**	0.008**	0.011**
Unemployment Rate[58]	-	-	-	-	0.163***
Neighborhood Area[59]	-	0.365***	-	0.342***	0.337***
Model Summary					
R^2	0.097	0.159	0.013	0.165	0.181
Adjusted R^2	0.096	0.157	0.011	0.162	0.177
Mean VIF	-	1.17	-	1.14	1.15
Largest VIF	-	1.17	-	1.22	1.24
Total # of neighborhoods	839	839	839	839	839

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

Model 3 presents the second independent variable for this analysis, measured as the relationship between varying levels of socio-economic inequality and 2013 neighborhood-level violent crime rates. These results suggest a positive and statistically significant relationship between this predictor and varying rates of violent crime, thus supporting previous research on the pervasive effect that increased levels of inequality have on violent crime victimization (Agnew, 1999; Blau & Blau, 1982; Krahn et al., 1986; Hipp, 2007). It is nonetheless important to mention the relatively weak explanatory power of this model, with only a 1% explained variance in the total variation of violent crime rates across Paris' neighborhoods during 2013. These results prompted the inclusion of an additional socioeconomic contextual variable (see Model 5) to continue advancing on the search of the main social correlates of violent crime victimization across Paris's neighborhoods.

[58] Square-root transformed to induce normality.
[59] Log-transformed to induce normality.

The current study's central hypothesis was tested in Model 4, which jointly analyzed how varying contexts of criminal risk and socioeconomic inequality interact with 2013 neighborhood-level violent crime rates in the city of Paris. As seen in Table 14, a positive and statistically significant relationship emerges from the current model, indicating that the two predictors have a positive and statistically significant relationship with the dependent variable. The explained variance of this joint model accounts for 16% of the total variation on 2013 violent crime rates across Paris's communities. These results build on previous research (see Drawve et al., 2016; Thomas & Drawve, 2018) by demonstrating how varying contexts of criminal risk and socioeconomic inequality are significant predictors of violent crime victimization rates in a major city like Paris. As indicated by the low mean and maximum VIF values reported in Model 4, the chances of multicollinearity are well below the acceptable limits (see Bernasco & Block, 2011), therefore, indicating the absence of multicollinearity problems with these data.

Lastly, Model 5 included an additional social variable for Paris's neighborhood-level unemployment rates. As expected, the two main predictors in the current study (i.e., crime risks and inequality) remained positive and significant after including a new predictor. This new social variable appeared to have a positive and statistically significant relationship with neighborhood-level violent crime rates in Paris. As with the previous two models, the reported VIF values for Model 5 indicate the absence of collinearity problems. These results extend previous research (see Chiricos, 1987; Raphael & Winter-Ebmer, 2001; Fougère et al., 2009) on the positive association between unemployment and crime. Moreover, this model explains 18% of the variation of Paris' 2013 violent crime rates, indicating that the presence of unique contexts of criminal risk, inequality, and unemployment are associated with an increase in the rate of violent crime victimization across communities in Paris.

Conclusion

In the early XIXth century, Guerry and Quetelet revolutionized the study of crime and place with their detailed analysis on the spatial characteristics of crime. Through the use of statistics, they demonstrated the association between varying social contexts and various types of criminal behavior. However, their research remained constrained by the use of large units of analysis, such as entire regions of France. Thus, they were unable to account for variations at smaller units of analysis. A century later, Stanciu (1968) proposed a micro-level study on the main social correlates of criminal behavior across the city of Paris. However, he missed accounting for the effect of the physical environment in explaining the increased likelihood of criminal behavior at these micro-level places. To continue expanding the current literature on the spatial determinants of crime in the city of Paris, the current study proposed studying how neighborhood-specific physical and social contexts can explain variations in violent crime rates across diverse environments.

The presence of unique contexts of criminal risk and socioeconomic inequality allowed us to explain 16% of the variation in violent crime rates across neighborhoods in Paris. As a result, improving the general understanding of varying contexts of criminal risk and inequality can help explain the spatial distribution of neighborhood-level crime rates across the city of Paris. However, while significant, the effect of inequality on violent crime rates remained weak, prompting the inclusion of an additional contextual variable. In this regard, it is important to note the presence of unique contexts of relative segregation in the city of Paris, given that segregated groups are more or less mixed residentially (Préteceille, 2012). Under such unique contexts of relative segregation, the pervasive effect of socioeconomic inequality on violent crime outcomes could be impaired by higher levels of social cohesion. As noted by Sampson et al. (1997), the association of contexts of social disorganization and residential instability with violence can be mediated by collective efficacy. Future research should further analyze the moderating effect that relative contexts of urban segregation present on the variation of neighborhood-level violent crime rates in the city of Paris.

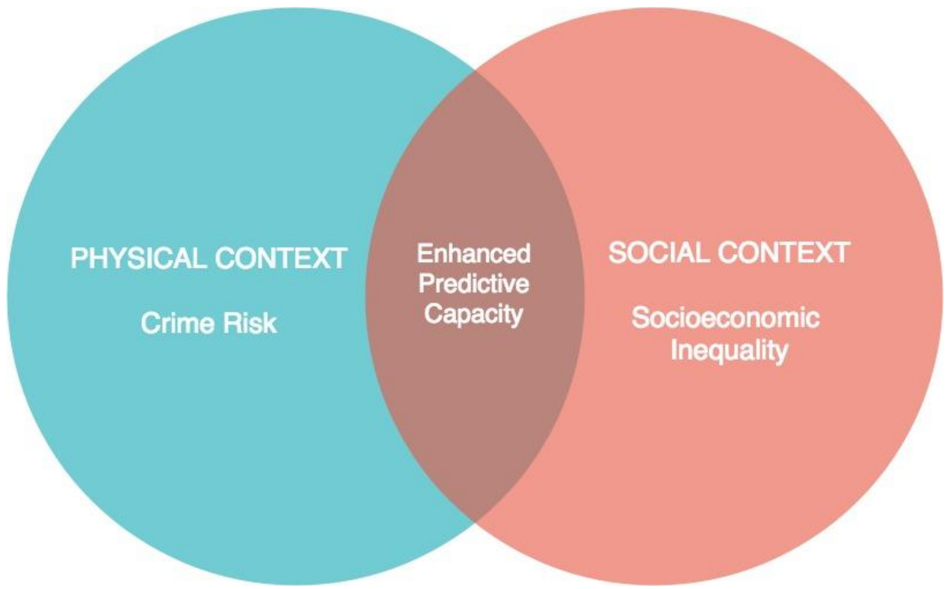
The final model presented the combined effect that contexts of crime risk, inequality, and unemployment have on the distribution of Paris's neighborhood-level violent crime rates. This last model increased the explained variance on neighborhood-level violent crime rates to 18%, thus, supporting the inclusion of additional socioeconomic contextual variables to continue advancing in the study of main correlates of violence and crime. The current study builds on the extant RTM research (see Drawve et al., 2016; Piza et al., 2016; Thomas & Drawve, 2018) by examining the main physical and social correlates of violent crime victimization rates in a relevant study setting such as Paris.

CHAPTER 8: A CROSS-NEIGHBORHOOD MULTI-JURISDICTIONAL COMPARISON, IMPLICATIONS FOR FUTURE RESEARCH, AND CONCLUSIONS

> *"I'm of those who believe that excesses in all matters are not a good idea, whether it's formation of bubbles, whether it's excess in the financial markets, whether it's excess of inequality, it has to be watched, it has to be measured, and it has to be anticipated in terms of consequences."*
>
> - Christine Lagarde

What is the relationship between community-level crime rates and varying contexts of risk and social disorganization? Nearly two centuries after the works of Guerry (1833) and Quetelet (1835), this question remains controversial. On the one hand, ecological theorists (Shaw & McKay, 1942; Blau & Blau, 1982; Messner, 1982; Williams, 1984; Sampson, 1985; Hipp, 2007; Kelly, 2000) claim that contexts of social disorganization and collective efficacy can explain variations in neighborhood-level crime rates. On the other hand, environmental theorists (see Brantingham & Brantingham, 1993; Cohen & Felson, 1979; Wortley & Mazerolle, 2008) claim that the physical environment is primarily responsible in creating unique contexts of criminal opportunity leading to expressions of deviant behavior. The current study proposed combining the theoretical frameworks of environmental criminology and social disorganization (See Figure 11) to study neighborhood effects on violent crime victimization rates. Few studies have followed this approach (see Drawve et al., 2016; Piza et al., 2017; Thomas & Drawve, 2018; Hewitt et al., 2018) by jointly studying the physical and social correlates of neighborhood-level crime rates.

Figure 11. The nexus between contexts of crime risk and socioeconomic inequality



The current analysis offers a novel approach to the study of neighborhood-level violent crime victimization rates by empirically testing the combined effect of unique contexts of crime risk and socioeconomic inequality across three distinctive urban settings. Bogotá's neighborhoods were analyzed in Chapter 4 to determine the interaction effect between varying contexts of crime risk and income inequality on community-level violent crime rates. As per the results of Bogotá's case study, both predictors (i.e., crime risk and inequality) appear to be highly correlated with the spatial distribution of violent crime rates across the city's neighborhoods. Next, in Chapter 5, the hypothesis of this study was tested across Chicago's neighborhoods. The results suggest that contexts of crime risk and socioeconomic inequality are once again associated with an increase in violent crime victimization rates across Chicago's communities. Lastly, in Chapter 6, Paris's community contexts were tested to measure the effect that risky environments and contexts of socioeconomic inequality present on violent victimization rates. Again, the results of Paris's case study support the main hypothesis of this study, given that the combined effect of both predictors was associated with an increase in violent crime victimization rates.

The main hypothesis of this study sought to test the combined effect that contexts of socioeconomic inequality and crime risk present on the spatial distribution of neighborhood-level violent crime rates. This analysis also assessed the separate effect that both predictors presented on the spatial distribution of violent crime rates across communities. By testing these two measures independently, this study was able to determine the level of association between physical and social contexts with the varying rates of violent crime victimization across neighborhoods in Bogotá, Chicago, and Paris. Ultimately, these allowed for comparisons to be made between the spatial association of contexts of inequality and crime risk, and the observed effect of their combined impact on victimization rates.

The results from this study confirm that the combined effect of the two predictors (i.e., crime risk and inequality) outperformed the "individual" predictive capacity of separately examining contexts of crime risk or inequality across these three case studies. These research findings not only support the enhanced predictive capacity of combining the study of social and physical contexts to better understand the spatial distribution of neighborhood-level victimization rates but also support the complementarity of these two measures. Therefore, this approach offers a unique opportunity to identify how neighborhood characteristics can influence the emergence of contexts of criminal activity.

This analysis presented three case studies offering a unique account of how variations in neighborhood-level physical and social correlates produce a direct and measurable impact on the spatial distribution of violent crime victimization rates. This was done through the lenses of a multi-jurisdictional study aimed at explaining how neighborhood characteristics in three major cities, from largely distinctive regions in the word, can help explain the distribution of violent crime rates. According to Sampson (1985), neighborhood characteristics, like poverty, inequality, mobility, or structural density, can help to predict the risk of victimization regardless of individual characteristics. Similarly, the current study assumed that neighborhood effects in cities such as Bogotá, Chicago, and Paris can be identified and measured to advance in the search of the primary physical and social determinants of violent crime victimization. With this objective in mind, the current study measured victimization rates across neighborhoods in all three cities and compared the spatial distribution of these criminal environments against the presence of unique contexts of socioeconomic inequality and crime risk.

In this comparative analysis, variations were expected to emerge based on the varying influences that contexts of crime risk and inequality present in the distribution of violent crime across different case studies. These variations are the result of unique ecological and societal differences that differentiate these geographies from one another. A reality addressed by Kennedy (1983), in which he explained using the example of a "kaleidoscope," how changes from one jurisdiction to another can reveal unique spatial and situational contexts that have implications for criminal behavior at these places. As a result, this study offers an approach that can be easily replicated in other jurisdictions, but whose effectiveness will depend on the correct selection of the most significant physical and social factors affecting deviant behaviors in each jurisdiction.

The Relationship Between Income Inequality and Violent Crime

This argument is well illustrated by the varying influences that contexts of socioeconomic inequality present across neighborhoods in all three geographies studied in this analysis. As seen in Table 15, large differences in victimization rates were found despite the presence of similar levels of neighborhood-level inequality across neighborhoods in the three study settings. In fact, significant variations were found in the explanatory power that these contexts present on the spatial distribution of violent crime rates. In Bogotá, the association between unique contexts of inequality and violent crime rates was more robust (Adjusted R square = 0.22) than in Chicago (Adjusted R square = 0.03) or Paris' case studies (Adjusted R square = 0.01), thus indicating that socioeconomic inequality emerges as a stronger predictor of victimization across Bogotá's communities than Chicago's or Paris's. These results are consistent with the positions of the city Bogotá within the Latin American context, the world's region with the highest levels of inequality (Eckstein et al., 2003; López-Calva et al., 2015) and violent crime victimization (UNODC, 2013).

Table 15. Comparing inequality levels across case studies

Indicator / Geography	**Bogotá**	**Chicago**	**Paris**
City-level Gini	0.54	0.53	0.5
Neighborhood-level Gini	0.37 – 0.59	0.25 – 0.72	0.27 – 0.68
Mean	0.46	0.45	0.44
Standard Deviation	0.07	0.07	0.06

From a comparative standpoint, the varying influences that contexts of inequality pose on violent crime outcomes could be explained by the moderating effect that varying macro-societal processes exert in these cities. In a recent study, Fujita (2012) found that urban segregation and class inequality patterns are sustained on the basis of: "Contextual differences in housing and labor markets, politics and policies, the role of the state, the welfare state, family networks, built environment, laws and values, and customs and norms" (p. 287). These societal processes have direct consequences on the presence or absence of segregated environments across geographies. Based on these institutional and societal differences, Fujita (2012) classified different world cities as "highly segregated and unequal" in cities like Sao Paulo in the Latin American region or Beijing, "moderately separated and unequal" in cities like Paris or Budapest, and "together and equal" in cities like Tokyo or Taipei. Such classification offers an overview on the macro-societal processes directly influencing segregation and class inequality patterns across different world cities.

For example, welfare state policies in countries like Denmark, Germany, or France can allow low income families and unemployed individuals to improve their living conditions, thus reducing social differences and limiting the chances of secluded neighborhoods. As previously noted, segregation patterns across France's capital are relative and not absolute with segregated groups distributed in largely mixed residential areas (Préteceille, 2012). An important distinction to consider when analyzing the impact that unique contexts of socioeconomic inequality present in the city of Paris to create environments that are conducive to violent crime. In these contexts of "social mix," the pervasive effects of inequality appear to be moderated by the presence of unique urban socio-spatial structures, resulting in a reduced impact of these environments on victimization rates across Paris's neighborhoods.

It is important to note that the current analysis was limited to the jurisdictional boundaries of the city of Paris,and did not include the extensive metropolitan area surrounding the city also known as the Paris "banlieue." It is in these communities surrounding the city of Paris where large numbers of unemployed young immigrants live in segregated neighborhoods, excluded from the labor market (Fujita, 2012). These neighborhoods have had in recent years important peaks of violence[60], particularly in the French Departement of Seine-Saint-Denis. Future analysis should include these study settings to continue advancing in the search for the main social correlates leading to violent crime victimization in Paris.

In other cities like Chicago or Bogotá, communities present characteristic patterns of highly segregated urban environments across their landscape, a distinctive reality compared to Paris' socially mixed communities. Still, the presence in these cities of secluded neighborhoods and mounting inequality respond to different reasons. On the one hand, the city of Bogotá shares Latin America's long-standing problem with the old colonial class structures and persistent residential segregation patterns (Fujita, 2012). A situation that has historically led to the creation of highly segregated environments as well as contexts of extreme inequality across class lines. In fact, the city of Bogotá is a city where different social classes are highly clustered in a number of specific urban areas. In this sense, richer neighborhoods concentrate in the northern part of the city, while low-income communities are highly concentrated in the southern sections of the city. This

[60] http://www.leparisien.fr/faits-divers/banlieues-comment-eteindre-le-feu-14-02-2017-6679302.php

spatial distribution of social classes clearly illustrates the existing level of residential segregation and socioeconomic inequality that has existed in Bogotá since the colonial times.

A different institutional set-up can explain the high levels of segregation and inequality in countries like the United States or the United Kingdom. In these geographies, liberalism and market competition forces often replace state-led intervention policies, leading to an increase in class confrontation (see Fujita, 2012). It is a case well illustrated through the example of the city of Chicago, considered to be among the most segregated cities in the United States (Musterd & Ostendorf, 2013), a city with a long history of racial segregation sustained by institutional and financial discrimination of minority groups, particularly African-Americans, a situation that limited the spatial mobility of these minority groups and which reinforced segregation patterns that still exist today across Chicago's communities. As noted by Musterd and Ostendorf (2013): "Spatial segregation of poor people, especially African-Americans in Chicago, is extreme and there is strong evidence to support the contention that it has compounded considerably their chances of moving up the social mobility ladder" (p. 59). A pattern of extreme segregation that, as seen by the results of the current study, leads to expressions of violence and crime, fueled by feelings of dissatisfaction and animosity towards society.

It is still important to note that even though the explanatory power of these models varied across case studies, all three models were highly statistically significant[61]. These findings support the need to continue examining the association between contexts of inequality and violent crime across neighborhoods. As previously noted, this is a social

[61] $p < 0.001$ (Bogotá and Chicago); $p < 0.01$ (Paris)

phenomenon that is expected to continue expanding as the gap between socioeconomic groups continues to grow in the future (Stiglitz, 2012). In this sense, it is fundamental to address possible institutional biases and discriminatory policies that exist across highly segregated environments to improve living conditions, thus reducing the chances of violence and crime to erupt in these communities.

Examining Risky Environments across Neighborhoods in Bogotá, Chicago, and Paris

The current study's second predictor sought to establish the association between risky environments and the persistence of increased levels of violent crime victimization rates across neighborhoods in three major world cities. As seen in Table 16, the relationship between contexts of crime risk and neighborhood-level violent crime rates appeared to be highly significant across communities in Bogotá, Chicago, and Paris. In fact, the explanatory power of the ANROC measure[62] on neighborhood-level violent crime rates was on average 21% across all three case studies. These results support the robust predictive capacity that modeling risky environments offers at explaining the spatial distribution of neighborhoods displaying high crime rates.

Moreover, these three case studies showed similar comparative levels of explained variance on the spatial distribution of victimization rates across neighborhoods in all three geographies. For instance, in the city of Bogotá, the ANROC measure was associated with 24% (Adjusted r-square = 0.24) of the variation on violent crime victimization rates. Similarly, in the city of Chicago, the spatial distribution of risky environments (i.e., ANROC) explained 23% (Adjusted r-square = 0.23) of the variation in victimization rates

[62] After controlling for neighborhood area size.

across the city's neighborhoods. These results accentuate the narrow difference of just 1% in the explained variances observed across Chicago's and Bogotá's case studies. Lastly, Paris's model showed a 16% (Adjusted r-square = 0.16) explanatory power on the relationship between contexts of crime risk and violent crime victimization rates. Overall, Paris's model showed the lowest explained variance across all three case studies but remained a significant predictor at explaining the variation of violent crime rates across Paris's communities.

Table 16. Comparison of results across case studies

Indicator / Geography	**Bogotá**	**Chicago**	**Paris**
City Population	7,878,773	2,702,471	2,220,445
Average Neighborhood Population (Total number of neighborhoods)	67,118 (111)	3,419 (797)	2,578 (839)
Relationship between contexts of *crime risks* on neighborhood-level *violent crime rates* (Adj. R^2)[63]	0.24	0.23	0.16
Relationship between contexts of *income inequality* on neighborhood-level *violent crime rates* (Adj. R^2)	0.22	0.03	0.01
Combined effect of *crime risks* and *income inequality* on neighborhood-level *violent crime rates* (Adj. R^2)	0.39	0.25	0.16

[63] These figures correspond to "Model 2" OLS regressions, in which neighborhood land areas were utilized as a control variable within the analysis.

To identify, measure, and compare how contexts of crime risk impact communities, it is fundamental to first model the spatial influences of the built environment in the proximity of crime incidents. With this objective in mind, the current study opted to use the Risk Terrain Modeling (RTM) technique, a method well supported by previous research (see Dugato et al., 2017; Garnier, Caplan, & Kennedy, 2018; Giménez-Santana et al., 2018; Kennedy et al., 2015). The RTM technique is rooted in the principles of environmental criminology (Brantinghman & Brantigham, 1993) and risk assessment (Kennedy & Van Brunschot, 2009). It is a method that allows to assess the spatial influences of the built environment against a series of crime attractors and generators (Brantinghman & Brantigham, 1995). As noted by Bernasco and Block (2011), the presence of crime generators and crime attractors (CGAs) can contribute in creating unique criminogenic. For example, CGAs used across the different case studies presented in this research included parks (Groff & McCord, 2012), schools (Roncek & Faggiani, 1985), or bars (Ratcliffe, 2012), among others. These locations are known to generate unique behavior settings in the proximity to these locations.

In modeling the effect of the built environment to measure neighborhood risk, this analysis has demonstrated how identifying risky environments (i.e., neighborhoods-at-risk) can help predict the spatial distribution of victimization rates across broadly diverse geographies. Thus, supporting this empirical approach in the study of neighborhood characteristics and the diverse effects of risky environments on crime.

The Nexus between contexts of Crime Risk and Socioeconomic Inequality

Lastly, the relationship between contexts of criminal risk and inequality was tested against the spatial distribution of neighborhood-level violent crime rates. This joint model allowed to explain, on average, a 26% of the total variation in victimization rates across neighborhoods in Bogotá, Chicago, and Paris. A result that validates the main hypothesis of this study, given that the presence of risky environments and varying contexts of socioeconomic inequality were positively associated with an increase in violent crime rates across all three study settings. The strong predictive capacity presented across these case studies support the appropriateness of using this approach in other geographies and across different world cities.

These findings are consistent with previous research by Drawve et al. (2016) and Thomas and Drawve (2018) on the suitability of using the RTM technique to build a measure of contextual crime risk (i.e., ANROC) to continue advancing the study of neighborhood effects on crime. In their research, Drawve and Thomas combined the use of ANROC with overlapping forms of socioeconomic resource disadvantage (e.g., contexts of poverty, racial inequality, etc.) to explain the distribution of aggravated assault counts in Little Rock, Arkansas. Similarly, Piza et al. (2017) found that the spatial influence of criminogenic features significantly varied across neighborhood contexts.

Similarly, the current analysis opted to study the interactive effect that unique contexts of crime risk and socioeconomic inequality presented on violent crime victimization rates across largely different urban settings. These results clearly demonstrate that varying physical and social contexts have an effect on violent crime victimization rates and that this effect varies across geographies. For instance, the joint model using ANROC and Gini was more predictive in Bogotá with an explained variance of 39% (Adjusted R-square = 0.39) than in Paris where the same model only accounted for 16% (Adjusted R-square = 0.16) of the variation in victimization rates. In Chicago's case study, the joint model predicted 25% of the total variation in neighborhood-level violent crime rates. These results suggest that the presence of unique contexts of socioeconomic inequality and crime risk produce varying effects across different geographies.

As seen in Table 16, the largest variation across case studies occurred regarding the impact that contexts of inequality had on the distribution of violent crime rates. As previously discussed, the association between the ANROC measure and the dependent variable was, for the most part, robust and constant across cases. From a comparative perspective, the variations presented by contexts of inequality across study settings had a large impact on the overall predictive capacity of the different joint models. For example, in Paris, the reduced, but significant impact that contexts of inequality presented in explaining the distribution of violent crime rates prompted the inclusion of an additional contextual variable for neighborhood-level unemployment rates. The inclusion of this contextual variable allowed to improve the explanatory power of the joint model. In other words, these findings suggest the importance of testing for additional contextual variables to account for macro-societal variations across geographies. Thus, indicating that a "one-size-fits-all" approach in determining the main social contexts for victimization isn't the most appropriate when studying variations in crime rates across largely different international urban settings.

Preventing Violent Crime through a Community-Based, Evidence-Informed Approach

The policy implications of this research study support the importance of scientific evidence in the development of community-based strategies to reduce crime and violence. This research has empirically demonstrated how varying contexts of crime risk and socioeconomic inequality associate with an increase in violent crime rates across neighborhoods in three large world cities. With this objective in mind, the identification of risky environments and unique contexts of inequality can help develop tailored strategies to mitigate the various risks posed by these neighborhood contexts.

In this sense, the approach developed by the current study can help to improve the management of risky environments to reduce crime and boost public safety. This can be achieved by implementing a comprehensive risk-based agenda that could benefit communities at risk. As noted by Caplan and Kennedy (2016, p. 118), "coupled with sustainable investments in human capital, smart data, continuing education, and current technology, risk-based policing can go a long way to help agencies fight and prevent crime." This objective can be achieved through interdepartmental cooperation between local authorities and other relevant stakeholders. For instance, by increasing engagement initiatives and improving access to local services. In fact, by identifying, through the use of this approach, the presence unique contexts of social disorganization and crime risk could positively impact the design of intervention strategies in a more sustainable way. Moreover, communities presenting contexts of crime risk should undertake extensive reviews to identify the nature of the physical features that increase the risk of victimization within these community environments. Once identified, different risk-based initiatives can help mitigate the varying influences created by these locations. For example, poor street lighting can be converted through the use of more efficient LED lighting to reduce the risk of victimization (see Painter, 1996; Clarke, 2008).

In Venezuela, the organization, “Caracas, Mi Convive”[64] (Translated from Spanish: Caracas, we coexist) pioneered in conducting crime prevention workshops across communities at risk in the city of Caracas. Their approach is simple; first, they identify hot spots of crime to target areas where they implement different risk mitigation programs. Then, using a crime prevention through environmental design (CPTED) approach (see Jeffery, 1977), they develop strategies aimed at deterring crime at these locations by recovering these spaces and empowering local residents. Some of their programs include organizing activities between young adults, parents and other residents, the recovery of public spaces, sports, and cultural events. This NGO and other similar organizations could benefit from this study’s approach in identifying communities at risk based on the presence of unique contexts of crime risk and inequality. As a result, this analysis presents interest groups and other local stakeholders an opportunity to understand better how neighborhood characteristics influence the persistence of crime.

In today’s big data era, the adoption of tools that can combine different data sources to find hidden insights has grown exponentially (see Ferguson, 2017). One of the most significant advantages for police agencies in the use of data-driven approaches involves the reduction of bias in their decision-making processes to boost transparency and accountability. As noted by Ferguson (2017, p. 19), “turning the page on human bias or racial discrimination became an important spur in the adoption of big data policing.” In this sense, the approach presented by the current study offers an innovative tool that uses

[64] http://miconvive.com/project/talleres-prevencion-violencia/

big data to produce criminal intelligence. Yet, the potential applications of this set of tools are not restricted to the study of crime and could extend to other fields like urban planning. For instance, future zoning decisions could be substantiated through the use of this approach to improve the situation for communities at risk.

Limitations & Future Avenues of Research

The current study has advanced the search of neighborhood effects on crime by identifying the presence of unique contexts of crime risk and socioeconomic inequality across communities in Bogotá, Chicago, and Paris. In identifying the physical and social determinants of crime at the neighborhood-level, it has provided an alternative explanation on the forces driving higher victimization rates across community environments. Still, the current study has only offered an aggregate depiction on the effect that neighborhood characteristics have on violent crime victimization.

It is important to note the variation in sample size between Bogotá's case study, presenting just 111 neighborhood divisions, and Paris' case study with over 800 neighborhood units. In other words, Paris' analysis captured a variation eight times higher than that of Bogotá's case study. From a comparative perspective, this difference in sample size posed a limitation for the current study. However, to limit the chances of obtaining biased regression estimates, the current study consistently used adjusted R-squared values to compare regression models across all three study settings (see Cramer, 1987).

Future studies should consider analyzing separately the spatial influences of different crime types like homicides, assaults, and theft incidents. In this regard, it is fundamental to also study the relationship between physical and social contexts linked to specific crime types to continue advancing in the search of the main drivers of victimization across changing environments (see Giménez-Santana et al., 2018; Thomas & Drawve, 2018). Furthermore, future avenues of research should consider analyzing the effect of unique contexts of crime risk and inequality on property crimes. Previous research (see Bourguignon et al., 2003; Demombynes & Ozler, 2005) found a positive association between contexts of inequality and an increase in property crime rates. Other research findings (see Allen, 1996) suggested otherwise, and found that inequality and social structure has no impact on property crime activity. Therefore, future studies should seek to examine the combined effect that unique contexts of crime risk and socioeconomic inequality present on the distribution of property crime incidents across neighborhoods.

The current study was also limited to the study of across neighborhood variations in inequality and crime risk, thus not accounting for within-neighborhood variations. Few studies (see Hipp, 2007; Kang, 2015) have addressed the relationship between local (within-neighborhood) inequality and varying crime rates. Kang (2015) found that the correlation between within-neighborhood inequality and crime was weak or negative. Conversely, Hipp (2007) discussed the importance of the distribution of within-neighborhood race and class as an important factor that explains the distribution of crime rates. Therefore, future research studies should seek to address the association between within-neighborhood inequality and crime risk with the presence of higher victimization rates; thus, expanding this analysis' research findings.

An important avenue of future research that was addressed, but not tested by the current analysis is the role that varying social contexts present as enablers or attenuators of the spatial influences created by the built environment. In other words, are the attracting qualities of a risky environment the same in a disadvantaged neighborhood than they are in a non-disadvantaged context? A recent study by Thomas and Drawve (2018) addressed this research question by analyzing the interactive effect that social structure and the physical environment present at the neighborhood-level in Little Rock, Arkansas. In their view, two distinctive processes can explain the interaction effect between social and physical contexts. On the one hand, an amplification process will suggest that the spatial influences from the built environment can be enhanced in disadvantaged neighborhoods; on the other hand, an attenuation process will explain the opposite effect, as the association between violence and enabling physical environments is weakened in disadvantaged neighborhoods. According to their results in Little Rock, the attenuation model suggests a moderating effect between the ANROC measure and varying contexts of structural disadvantage (Thomas and Drawve, 2018). Therefore, future research studies should analyze the interactive effect between neighborhood contexts of crime risk and socioeconomic inequality on the spatial distribution of victimization rates.

Lastly, the study of criminology is subject to a series of limitations due to the very nature of crime data and how these are obtained and processed in the field. As noted by Weisburd and Piquero (2008): "overall, there is a great deal of unexplained variance in crime" (p. 457). According to their research findings, the level of variance explained in criminology papers is often very low, with as much as 80 to 90% of unexplained. As a result, a significant variation in crime still remains unexplained by current research studies. A major factor contributing to the difficulty at explaining crime variations is the fact that crime data tends to be of poor quality and is subject to a series of biases from police agencies across different countries (Bourguignon, 1998). For example, data manipulations can try to hide police underperformance, corruption, or relying on community-based internal justice, and are all known as factors that contribute to lower data accuracy and reliability. It is therefore important to note the limitations that exist at explaining variations in crime and how this may impact results across studies.

Conclusion

Building on the extant literature on neighborhood effects on crime (see Sampson, 1985, 2012; Morenoff et al. 2001), this study contributes to close the existing theoretical gap by identifying the presence of unique contexts of crime risk and socioeconomic inequality. Under the premise that crime is not randomly distributed in time and space (Cohen & Felson, 1979), this research analyzed how communities presenting unique physical and social contexts are associated with an increase in violent crime activity. This approach was examined in a comparative analysis across neighborhoods in the cities of Bogotá, Chicago, and Paris. As a result, it was empirically demonstrated how a combination of contexts of crime risk and socioeconomic inequality could explain the distribution of violent crime victimization rates across largely diverse geographies. This is an approach that can be easily replicated across neighborhoods in a variety of environmental settings using a wide range of social contexts.

Previous ecological studies (see Park et al. 1925; Shaw & Mckay, 1942; Sampson; 1985) have long overlooked the importance of accounting for the influence of the built environment in attracting and generating deviant behaviors. To date, vast literature supports the predictive capacity of the Risk Terrain Modeling technique (see Kennedy et al. 2015; Drawve, 2016; Dugato et al. 2017; Garnier et al., 2018), and suggest applying

RTM to the study of a variety of environmental factors, as well as how these create unique behavior settings for criminal activity. In this regard, the current study has demonstrated how identifying risky environments using ANROC can allow people to make accurate predictions on the distribution of future crime rates.

However, the role of the physical environment in explaining crime can't be fully understood without accounting for the presence of unique social contexts that create the necessary conditions for crime to occur. Therefore, this analysis opted to combine the theoretical frameworks of environmental criminology and social disorganization to study how varying neighborhood's physical and social contexts impact the distribution of violent crime rates. As previously noted, variations in the social structure of entire neighborhoods can influence the attracting qualities of the built environment in creating contexts of criminal opportunity (see Thomas & Drawve, 2018).

With this objective in mind, the current analysis demonstrated how unique contexts of socioeconomic inequality present varying influences on the distribution of victimization rates across different geographies. As expected, inequality across Bogotá's neighborhoods was highly associated with the distribution of violent crime rates. In the city of Chicago, a positive relationship was found between unique contexts of income inequality and varying rates of violent crime. However, additional social contexts will need to be examined in future models to continue advancing in the search for the main social forces driving criminality across Chicago's communities. In Paris, the presence of unique contexts of inequality across the city's neighborhoods was associated with a small, but significant relationship on the distribution of violent crime rates. It is therefore important to understand how institutional, regional, and societal differences across geographies can influence the overall effect that unique contexts of socioeconomic inequality present on the persistence of contexts of criminal activity.

Therefore, by improving our understanding of the main social contexts driving neighborhood criminality, we can design effective strategies directed at reducing these damaging contextual effects. In this sense, it is fundamental to examine the spatial influences of the built environment to improve our knowledge of how the physical environment attracts and generates deviant behaviors within these community-environments. It is important to note that the spatial influence of these physical features should continue to be measured at the micro-level (see Stanciu, 1968; Caplan & Kennedy, 2016), but its effects, as demonstrated, can be extrapolated at the neighborhood-level using ANROC (Thomas & Drawve, 2018) to better model the contextual effects created by other societal factors such as inequality. As a result, neighborhoods presenting unique sets of social and physical characteristics will be more likely to display higher victimization rates than neighborhoods not presenting these criminogenic environments. These results confirm the enhanced predictive capacity of combining the study of community-specific physical and social contexts to continue expanding the study of neighborhood effects on crime.

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