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Communities, Streets, and People: A Multi-level Study of the Correlates of Victimization

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Abstract

The current study adds the context of the immediate microgeographic environment (measured as the street segment) to the study of individual victimization. Using residential survey and physical observation data collected on 449 street segments nested within 53 communities in Baltimore, MD, we employ multilevel logistic regression models to examine how individual risky lifestyles, the microgeographic context of the street, and community level measures influence self-reported property and violent crime victimization. Results confirm prior studies that show that risky lifestyles play a key role in understanding both property and violent crime victimization, and community indicators of disadvantage play a role in explaining violent crime victimization. At the same time, our models show that the street segment (micro-geographic) level adds significant explanation to our understanding of victimization, suggesting that three level models should be used in explaining individual victimization. The impact of the street segment is particularly salient for property crime.

Keywords

microgeographic places; risky lifestyles; routine activities; concentrated disadvantage; street segments; victimization

Introduction

Within routine activity and lifestyle theories, there is wide agreement that individuals' lifestyles and the extent to which they engage in risky behaviors are strong predictors of individual victimization (Dong, Morrison, Branas, Richmond, & Wiebe, 2020; Gottfredson, 1984; Hindelang, Gottfredson, & Garofalo, 1978; Osgood, Wilson, O'Malley, Bachman, Johnston, 1996; Reisig & Golladay, 2019; Schreck, Stewart & Osgood, 2008). Lifestyles

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that involve unstructured or risky activities such as frequenting bars, using drugs, or engaging in criminal activities, place individuals in situations and contexts that increase their exposure to motivated offenders or places with less guardianship, subsequently increasing their risk of victimization.

Research that examines contextual effects on victimization has primarily been restricted to community-level studies (Felson & Boba, 2010; Miethe & Meier, 1990; Rountree, Land, & Miethe, 1994; Turanovic, Pratt & Piquero, 2018). Communities with different structural characteristics, such as concentrated disadvantage, have varying levels of opportunistic places, such as bars and liquor stores that are more or less conducive to crime including exposure to potential offenders (Miethe & Meier, 1990). This work, however, has not considered the local context of the street segment where individuals reside. There is a growing literature that identifies how characteristics of microgeographic places, particularly physical features, such as land use and use of public space, impact locations of crime and where it concentrates (e.g. see Groff & Lockwood, 2014; Hipp & Kim, 2019; Irvin-Erickson & La Vigne, 2015; Snowden & Freiburger, 2015; Weisburd, Groff, & Yang, 2012; 2014; Weisburd, White, Wire, & Wilson, 2021). Arguably, the daily routine activities on the streets where individuals reside, such as the patterns of movement associated with catching a bus or going to work, are influential in shaping individuals' risk for victimization. Opportunity structures at this microgeographic level are experienced directly, more so than broad community characteristics; however, little research accounts for these routine activities and movements of people in microgeographic places using primary data. Furthermore, research on microgeographic places typically uses official crime data, such as calls for service, as the outcome measure of crime, which is quite a different from individuals' reported victimization. In turn, the study of microgeographic places has largely ignored victimization questions.

To our best knowledge, this is one of the first studies to examine the characteristics of residents and the routine activities on the street segments they live on, while also accounting for the influence of structural characteristics of the community. Although researchers have theorized about how these various levels impact people's risk of victimization (Miethe & Meier, 1990; Turanovic et al., 2018), research has been limited in its ability to test whether existing explanations for victimization play out when all three-levels are accounted for, particularly the microgeographic place and community context together. Using a unique set of data collected from individuals nested within street segments that are nested within communities, we perform multilevel mixed-effects models to examine the unique role of individual-, street-, and community-level processes on risk of victimization. We question the extent to which street-level routine activities impact property and violent victimization on the street, and whether individual characteristics and structural disadvantage of the community have similar impacts on victimization, that is consistent with prior research, when accounting for the routine activities on the street.

Furthermore, the current study uses a rich set of measures of the street environment as reported by residents and observed by researchers. While using self-reported measures of victimization is not novel, we argue that measuring the routines of the street environment, as well as behaviors and use of public space as reported by residents, provides a new perspective on places that cannot be captured with census or secondary land use data. Residents of street segments are closely tied to the street they live on, and this context may play an important role in people's risk of victimization compared to the broader community-context, as exposure to motivated offenders and lack of capable guardianship may be in closer proximity to the residences of individuals.

Theoretical Background

Routine activity theory has long been used to explain the occurrence of crime and victimization through the convergence of motivated offenders, suitable targets, and lack of capable guardians in time and space (Cohen & Felson, 1979). At the individual level, this perspective has been expanded to explore and account for the influence of individual lifestyles and routines on risk of victimization (Hindelang et al., 1978; Osgood et al., 1996; Reisig & Golladay, 2019; Schreck et al., 2008). Drawing from Hindelang et al.'s (1978) original lifestyle theory, research has since found that age, race, gender, and lifestyles that involve working, being married, or having children impact how and with whom an individual spends their time, subsequently altering their risk of victimization (Arnold, Keane, & Baron, 2005; Bunch, Clay-Warner, & Lei, 2015; Felson, 1987; Hindelang et al., 1978; Kennedy & Forde, 1990; Cohen, Kluegel, & Land, 1981).

This area has evolved to include more direct measurement of "risky lifestyles" beyond demographics and conventional lifestyles, such as engaging in activities like frequenting bars, walking home alone at night, using drugs, and participating in criminal and other analogous behaviors. There is strong empirical support that these activities increase the likelihood of victimization, particularly violent victimization (Berg, Steward, Schreck, & Simons, 2012; Felson & Burchfield, 2004; Lauritsen, Sampson, & Laub, 1991; Lauritsen & Rezey, 2018; Turanovic & Pratt, 2014). Engaging in unstructured activities exposes individuals to risky environments that lack capable guardians, where the presence of motivated offenders is greater, and where the individual is perceived as a more suitable target (Berg & Loeber, 2011; Osgood et al., 1996). Importantly, individuals' lifestyles cannot be isolated from the environmental context; the reason risky lifestyles and behaviors have been so important for explaining risk of victimization is that these behaviors locate individuals in certain places where the situational and environmental contexts are conducive to crime and victimization. This is particularly relevant to property crimes that typically occur at an individual's home such as burglary or vandalism, and where offenders assess the opportunity structure of the place in their decision-making process (see Bernasco, 2010; Rountree et al., 1994; Wilcox, Madensen, & Tillyer, 2007).

Theorists and researchers have long aimed to understand where and why crime occurs in certain places as well as how the environment influences people's behavior (Brantingham & Brantingham, 1995; Weisburd, Bernasco & Bruinsma, 2009). For instance, drinking alcohol or drug use is often associated with risky lifestyles, but the behavior itself is not necessarily risky (see Reisig & Golladay, 2019). Rather, the risk is often associated with the times and places where drinking typically occurs—in bars at night where others are also drinking (Ratcliffe, 2010; Roncek & Maier, 1991). It is not only informative to understand how individuals' behaviors affect their own risk of victimization, but also how the immediate environmental context poses elements of risk can that inform why victimization is more likely to occur in certain places.

Community Contextual Effects—Macro-level research has examined how community characteristics shape risk of victimization more broadly from a number of theoretical perspectives (Miethe & Meier, 1990; Kennedy & Forde, 1990; Rountree et al., 1994; Sampson & Wooldredge, 1987; Turanovic et al., 2018). In a seminal article on routine activities and crime, Cohen and Felson (1979) emphasized the role of macro-level processes that structure activities and affect risk of victimization. Structural characteristics of communities and broad social changes, impact the different components of a crime event (suitable target, motivated offender and lack of guardianship) and how they merge in time and space, subsequently affecting crime rates even without increases in motivational risk factors (Cohen & Felson, 1979)

Social disorganization theory argues that a lack of informal social control and inability of residents to regulate behavior that arises in structurally disadvantaged communities is essential for explaining crime and victimization (Bursik & Grasmick, 1993; Kornhauser, 1978; Shaw & McKay, 1942). A lack of informal social control also contributes to the convergence of motivated offenders, suitable targets and guardianship (Kennedy & Forde, 1990; Sampson & Wooldredge, 1987; Smith & Jarjoura, 1989). For example, informal social control implies a degree of capable guardianship, such as those watching out for their home and neighbors, and intervening in issues on the block. Aspects of socially disorganized communities may hinder capable guardianship, as residents are less willing to communicate with neighbors and intervene in problems (Miethe & McDowall, 1993; Yuan & McNeeley, 2016; Saegert & Winkle, 2004).

Research has also examined the multilevel nature of these theories, examining the unique contribution of individual and community characteristics (Miethe & McDowall, 1993; Rountree et al., 1994; Sampson & Wooldredge, 1987). This research focuses particularly on disadvantaged communities where structural characteristics have a strong influence on individual lifestyles and exposure to motivated offenders, and where involvement in crime may be a way to support oneself or maintain social status in criminal subcultures, subsequently increasing the risk of victimization (Berg & Loeber, 2011; Jennings, Higgins, Tewksbury, Gover, & Piquero, 2010; Pyrooz, Moule, Decker, 2014).

Research on microgeographic places such as the location and situational context of a crime event, however, has been limited to official crime data (e.g. see Bernasco & Block, 2011; Boessen & Hipp, 2015; Groff & Lockwood, 2014; Haberman & Ratcliffe, 2015; Hipp & Kim, 2019; Irvin-Erickson & La Vigne, 2015; Snowden & Freiburger, 2015; Weisburd et al., 2012). More specifically, the study of contextual effects on victimization has been restricted to larger, community-level units of geography because victimization data is not readily available at a micro-geographic level. Thus, self-reported victimization has not been examined from the crime and place perspective, so it is relatively unknown how microgeographic places, particularly the street one lives on, impacts upon individual victimization.

The Role of Place—Over the past few decades, a strong body of evidence has established that crime is highly concentrated at microgeographic places (Andresen, Linning, & Malleson, 2017; Braga, Papachristos, Hureau, 2010; Pierce, Spaar, & Briggs, 1988; Sherman, Gartin, & Buerger, 1989; Weisburd, Bushway, Lum & Yang, 2004; Weisburd, Groff & Yang, 2012; 2014, Weisburd, 2015). Places with high crime concentration have been examined within the context of routine activity theory and other opportunity theories, particularly focusing on land use in urban areas and opportunity structures that are conducive to crime events, rather than the routines of people. Places with public transportation stops and transit centers where many people may be located, or commercial areas and establishments that increase pedestrian traffic, such as stadiums and shopping centers, influence the probability of victimization by altering levels of exposure and proximity to high risk environments and motivated offenders, as well as levels of guardianship (Browning & Jackson, 2013; Farrington & Welsh, 2002; Groff & Lockwood, 2014; Irvin-Erickson & La Vigne, 2015; Jones & Pridemore, 2019; McCord & Ratcliffe, 2009; Miethe & Meier, 1990; Sampson & Wooldredge, 1987). Certain types of places like schools, bars and taverns, liquor stores, check-cashing stores, convenience stores, and public housing have been found to attract or generate crime (Bernasco & Block, 2011; Roncek & Maier, 1991; Weisburd et al., 2012). A more recent study examined housing types and age of the housing on different types of crime, finding that large apartment buildings tend to generate more crime than streets with single-family homes (Hipp, Kim, & Kane, 2019). In another recent study, Jones and Pridemore (2019) had access to unique data at the street segment level that included a host of land use measures and aspects of routine activities such as CCTV cameras and security alarms, but again this study was limited to official city and police data. From this perspective, the primary focus is not on the behavior or victimization of individuals, but on describing the aspects of the environment immediately surrounding the crime event as they relate to the convergence of motivated offenders, suitable targets, and lack of guardianship.

Research has more recently attempted to capture the movement of people by examining temporal changes and spatial distribution of crime in microgeographic places, as these patterns arguably change opportunities of crime by altering aspects of guardianship, target suitability, and motivated offenders (Bernasco, Ruiter, & Block, 2017; Haberman & Ratcliffe, 2015; Irvin-Erickson & La Vigne, 2015; Ratcliffe, 2010; 2012). Measures of employees and businesses on streets influence travel patterns of individuals as they visit different places throughout their daily pattern, forming eco-networks in the community that may inhibit or encourage criminal activity (Bernasco et al., 2017; Brantingham & Brantingham, 1995; Browning, Calder, Boettner, & Smith, 2017; Hipp & Kim, 2019; see also Jacobs, 1961). Overall, these studies highlight the importance of commercial places and different types of business establishments that structure people's routines and patterns of activity on the street, subsequently altering opportunities for crime. Yet, they are limited to land use data and a relatively small number of covariates, primarily different types of places on the street, and used official crime data rather than self-reported victimization, which is an important contribution of the current study. We may expect these environmental characteristics of residential streets to also apply to victimization, but this remains an empirical question.

Furthermore, little attention has been given to residential streets where this "micro-community" typically exists. Since land use measures collected by the city typically pertain to building use and commercial activity, we know less about street segments that have few land use measures from the city. If there are not businesses on a street or a bus stop, how do we come understand the movement of people in these places? At a broader community level, we can get sense of this activity and movement of people, but it lacks specificity of activity on the street. As previously highlighted, Jacobs (1961) argued that the activity associated with businesses provide "eyes on the street" or informal social control, suggesting the importance of the street environment, but again, it does not account for "eyes on the street" in residential places.

While the definition of a microgeographic place varies across studies, including street segments (Weisburd, Bushway, Lum, & Yang, 2004; Weisburd et al., 2014), block corners and intersections (Braga et al., 2010; McCord & Ratcliffe, 2007), or street faces or blocks (Kurtz, Koons, & Taylor, 1998; Taylor, 1997), the street segment is an increasingly more common unit of analysis for micro place studies (Weisburd, 2015). Unlike the census block which captures data from four distinct street settings (Weisburd et al., 2009), street segments capture the visible social environment for facing streets. Weisburd et al. (2012) argued that street segment is more aligned with theories surrounding crime and place in which a crime event is more visible on the street one lives on. What occurs around the block, as well as the physical characteristics, may be quite different and not experienced by the resident (also see Andresen & Malleson, 2011; Steenbeek & Weisburd, 2016). Thus, measuring the routines and activities of people sharing this common space of residential streets and empirically testing the role of such patterns of behavior on victimization at microgeographic places remains underdeveloped. With the development of more advanced spatial analyses, researchers are able to explore various spatial units and provide further empirical tests of social ecological theories. Kim (2018) and Hipp and Kim (2019) apportioned census block data to street segments to assess its usefulness to measure street-level processes (Kim, 2018), and examine temporal patterns of crime at microgeographic places (Hipp & Kim, 2019). This method, however, does not account for heterogeneity of block faces on the same block, assuming the four sides of a block has the same features.

In summary, research recognizes that individual lifestyles matter particularly for understanding violent victimization. Additionally, high levels of concentrated disadvantage in communities increases the risk of victimization. At the same time, environmental research highlights the importance of opportunity structures at the micro geographic level in explaining violent and property crime. However, due to limited data collected at the microgeographic level, particularly self-reported victimization, little research has been able to examine how opportunity structures impact one's risk of victimization occurring on the street they live on, much less the impact of multiple levels of spatial units simultaneously. Our paper addresses these gaps in the literature with a large set of opportunity measures collected from residents at street segments, while also accounting for the importance of individual and community-level factors.

Current Study

We used street segments, intersection to intersection, as our microgeographic unit. There is a strong body of literature that suggests that street segments are not only an easy to define geographic unit but also one that has strong theoretical grounding as a behavioral unit of analysis; street segments do not simply represent physical entities, but are also social settings that can be understood at small-scale communities (Weisburd et al., 2012; see also Taylor, 1997; Weisburd et al., 2014, 2015; Weisburd, Shay, Amram, & Zamir, 2017; Wicker, 1987). Wikström (2006) described micro-places as the setting where an individual can "access with their senses" such as seeing and hearing (p. 87). The environment that residents can "see and hear" is the one outside their door, unlikely extending beyond the street they live on, such as around the block. When thinking about your neighbors, your frame of reference is likely the neighbors living next door, across the street or down on the corner—those who you are more likely to have social interactions with, rather than the people that live a few blocks away (Boessen & Hipp, 2015). Lastly, people who live on or even frequently visit a street segment, such as to catch the bus or walk the dog, may get to know one another and become familiar with each other's routines like going to work or parents taking their children to school; their movements become habitual and predictable, forming standing patterns of behavior on the street (Wicker, 1987). In this context, we can see street segments as not only microgeographic places, but also as "micro-communities."

Methodology

Data—The data used in the current study were obtained as part of a larger project (The Baltimore Longitudinal Study of Community Health and Anti-Social Behavior at Crime Hot Spots) that began in 2012, funded by the National Institutes of Health (Weisburd, Lawton, Ready, & Haviland, 2011). They study included a large residential survey of 3,738 residents living on 449 street segments in Baltimore City, Maryland conducted in 2013–2014. Baltimore is a large city on the Eastern seaboard with a population of over six hundred thousand people living within 92.1 square miles (U.S. Census Bureau, 2010, 2016). Although violent crime in the city has declined significantly since the mid-1990s, the violent crime rate in Baltimore City at the initiation of the study was nearly four times the national average (City Data, 2012). The intensity of violent crime and drug problems in the city was a key reason for its selection as a study site. A large sample of high rate crime hot spots was identified that could then be compared to streets with much lower crime levels.

Sampling streets—The sample was selected through a multi-stage cluster sampling procedure.[1] We began with the population of street segments in Baltimore (N=25,045) and linked crime call data to each street segment in the city for 2012 (the selection year for our study sample).[2] For purposes of the primary study, identifying crime hot spots for the sample was essential. Since by definition such places form a small proportion of places in the city, we set as a threshold of the top 3 percent of street segments for the highest number

[1]A detailed description of the sampling approach and methodology for the project is available online: https://cebcp.org/wp-content/uploads/2020/07/NIDA-Methodology.pdf.

[2]Crime call data for 2012 were obtained from the Baltimore City Police Department and geocoded to the street centerline. They were then spatially joined to obtain counts of crime for every street segment in Baltimore City. The geocoding match rate for the crime call data was 98.8%.

of calls for violent and drug crime.[3] This led to three categories of crime hot spots: violent crime hot spots, drug crime hot spots, and "combined" hot spots that met the criterion for both violent and drug crime. In order to collect an adequate amount of surveys on each street, only street segments with a minimum of 20 or more occupied dwellings units were included.[4] This reduced the sampling frame to 4,630 street segments.[5]

Hot spot street segments were then randomly sampled from their respective hot spot category.[6] A group of "non-hot spot" streets that did not meet the criterion for a crime hot spot were also selected randomly. Based on a review of the distribution of crime calls on these "non-hot spot" streets, streets with three or fewer crime calls for drug or violent crime were defined as "cold" spots. The remaining non-hot spot streets are defined as "cool spots" in our study. The final sample of street segments consisted of 47 cold spots, 100 cool spots, 121 drug hot spots, 126 violent hot spots, and 55 combined drug and violent crime hot spots. The descriptive data on crime and disorder calls for the sample of street segments, by type, are reported in Table 1 and a map of the sampled street segments is provided in Figure 1.

Table 1 demonstrates the high levels of crime in the hot spots compared to the cold and cool spots. Combined spots had the highest levels of crime, with an average of more than 30 violent crime calls in the selection year, nearly 75 drug crime calls, and over 250 crime and disorder calls all together. This may be compared with the cold spots, which have only a mean of 1.45 violent crime calls, and .19 drug crime calls.

Single family homes were more likely located on the cold streets, with an average of 6 single family homes, compared to roughly 1 single family home in hot spots. Alternatively, hot spots had a mean of 38 row homes, compared to 23 row homes on cold spots. Hot spot residents were predominately Black (82%), compared to 42% Blacks in cold spots. There were also large differences in employment rates (71% of residents living in cold spots were working full-time or part-time, compared to combined hot spots, where roughly 44% were working full- or part-time). The mean age was similar across the types of street segments, but hot spots had a greater percentage of female respondents. The cold streets also had a greater percentage of residents that were married (38%) compared to the hot spots (19%). On the social disorder scale (described below) combined hot spots had a mean of 2.9, while cold spots had a mean score of 1.25 (scale ranges from 1–3.22). In cold spots, the mean number of vacant dwelling units was 4.8% compared to 16% in combined hot spots.

While differences were notable across the types of street segments, hot spot streets were not always readily apparent by the environment of the street—a drug street in our sample on the East side of Baltimore was a poor, working-class street with about 33% of the residents

[3]Violent crime calls for service included rape (force), robbery (armed or unarmed), bank hold up, aggravated assault (cutting, hands, or gun), common assault, carjacking, abduction, and sniper. Drug crime calls included narcotics, narcotics outside, and narcotics on-view.

[4]We used data obtained from the Baltimore City Mayor's Office for year 2010 to identify occupied households on city streets.

[5]Due to our sampling criteria for residential streets (20+ dwelling units), streets located in the inner harbor, which are largely businesses and commercial, were not eligible for sampling.

[6]Streets were selected through a random sampling procedure developed in Model Builder (in ArcGIS) that prevented any two sample streets from being within a one block buffer area. Once residential street segments were selected based on these data, occupancy of dwelling units was verified through a physical census conducted by field researchers using a series of vacancy indicators. Streets were replaced in this process as needed to reach our sample goals.

not working and the residents were predominately black (88% in our sample). However, this street had few vacant homes, the yards were well-maintained, and streets and alleys were very clean. Researchers also reported that "people were very friendly on the block." This compares to another drug hot spot only four blocks away that had many signs of disorder, roughly a third of the households were vacant, 50% of the respondents were not working, and 70% of the residents were black. On the social disorder scale the latter street had a score of 2.77, compared to the former street with a score of 1.39. Researchers noted that there was lots of garbage in the alleys and a store owner complained of rats in the abandoned property next door.

We recognize that our over-sampling of crime hot spots leads to a sample of places that includes a much higher number of hot spots than would be included had we sampled streets randomly from the full sample of street segments. At the same time, it is important to recognize that a large number of streets in the city have little or no crime. Looking at the full sampling frame of residential streets only, 86.4% of streets did not meet the criteria for a hot spot, meaning that a large proportion of our sample would have had little if no crime during the selection year if we had used a simple random sample approach. Had we sampled randomly, only a handful of crime hot spots as we define them would have been included. This sampling frame in turn, likely provides a larger number of people who experience victimization than would have been the case had we randomly sampled streets in the city. In fact, even when using a sample of individuals living on streets with the highest levels of crime, less than 5% of our sample of individuals experienced violent victimization in the past year, and only 2.7% of these violent victimizations occurred on the street. Furthermore, 83% of those violent victimizations that occurred on the street were crime hot spots. While there is more property victimization experienced in our sample (22%) and it is more evenly distributed across types of streets, we think our original sample design provides a stronger and more robust baseline of victimization, while also including many streets where victimization was rare.

Sampling Households—Once the sample of street segments was identified, the next stage of sampling households was conducted. Trained field researchers visited each street to conduct a physical census of the street to identify any unusual barriers that would alter the street segment setting (e.g. bridges, alleys). Additionally, the field researchers documented the addresses of dwelling units on the street and verified occupancy through a number of vacancy indicators such as boarded up doors and windows or eviction orders. The list of occupied households provided the sampling frame of households for the residential surveys. The total number of dwelling units on the sampled street segments ranged from 20 to 310 units, and the mean number of occupied dwelling units 48 (SD=35 units). The mean length of the street segments in the sample was 577 feet (SD= 273 ft) ranging from 125 ft to 2000 ft with longer streets typically located in the outer areas of the city. Pairs of field researchers also conducted physical observations on the street to measure the physical environment and land use, such as building counts, uses, and vacancies, as well as aspects of disorder like broken windows, graffiti, and litter. A random sample of residences on each street was then selected with a goal of 7–10 surveys per street segment. Face-to-face surveys were conducted with the first adult resident, over 21 years of age, who also lived on the street for at least three months agreeing to participate in the survey. After accounting for abandoned houses and documented vacancies, the contact rate during the first wave was 71.2% and the cooperation rate was 60.5%.[7] The mean number of completed surveys collected per street was 7.7, ranging from 4 to 14 and the final sample consisted of 3,738 individuals from the 449 street segments. The study was approved by the IRB at George Mason University.

In addition to primary data collection on the sample of street segments, we used secondary data to supplement and provide additional contextual measures of the community. The Baltimore City Department of Planning and Baltimore Data Collaborative divided the city of Baltimore into 55 Community Statistical Areas (CSAs) to be more consistent with perceived neighborhood boundaries.[8] The communities defined by these boundaries are recognized by city planners, institutions, and residents, and are often used for the purpose of social planning and tracking trends in city conditions and demographics. Additionally, CSAs are commonly used in community research across a number of disciplines (e.g. see Gomez 2016; Merse, Buckley, and Boone 2008; Weisburd, White, and Wooditch, 2020; Weisburd, White, Wire, & Wilson, 2021). The Baltimore Neighborhood Indicators Alliance —Jacob France Institute (BNIA-JFI) aggregates census data at the tract-level to Community Statistical Areas (CSA). The CSA serves as the community-level unit of analysis for the present research (see Analytic Strategy below). The CSAs are shaded in the map in Figure 1. We used census measures of Community Statistical Areas drawn from the BNIA to capture structural variables at the community level. While we think that the CSAs, which were defined to identify community areas, is the best community level unit for our analyses, we also ran sensitivity tests using census tracts which define smaller areas of communities.[9]

Measures

Dependent Variables: The two dependent variables of interest included in the study are based on respondents' self-reported property and violent victimization that they experienced on the street segment. For *property victimization* we combined two items—1) whether anyone had broken into their home in the past year and 2) whether anyone had stolen something from their porch, yard, driveway or somewhere else outside their home in the past for a single binary measure (1=yes; 0= no). To measure *violent victimization* respondents were asked, "In the past year has anyone used violence against you—like in a fight, mugging, or physical assault?" This was followed up with a question about where the *last* incident took place—in your home, on your block, in your neighborhood, at work, or somewhere else. Given our focus on street segments, we limited *violent victimization* to only those incidents that occurred "on your block" or "in your home", dichotomously coded (1=yes; 0=no).[10]

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[7]The contact rate was calculated by dividing those households with contact/eligible households, and the cooperation rate was calculated by dividing households with a completed survey/households with contact. The average number of visits to households was 4, but we visited as many as 25 times in order achieve a high contact and cooperation rate.

[8]Four guidelines were followed when constructing CSAs; 1) the boundaries had to align with Census Tracts, 2) consist of 1–8 tracts with populations ranging from 5,000 to 20,000, 3) define relatively homogenous areas, and 4) reflect the boundaries of communities recognized by city planners, institutions, and residents (Baltimore Neighborhood Indicators Alliance, 2018).

[9]One distinct methodological problem with using census tracts, is that 50 of the sampled streets are located on census tract borders. Furthermore, of the 200 census tracts in Baltimore, 50 were not represented in our data because they had no sampled street segments, 49 census tracts had one street segment, and 36 census tracts had two sampled street segments located in the census tract, making it problematic to aggregate to this unit of analysis. We note that census tracts were not defined to create community areas, but for administrative purposes (e.g. see Weisburd, Bernasco, & Bruinsma, 2009).

Independent Variables

Individual-level characteristics.: We included several measures at the individual-level to capture aspects of individuals' lifestyles and behaviors, as well as a number of covariates such self-control and demographic variables that are related to lifestyles and victimization (Bunch et al., 2015; Schreck, Wright & Miller, 2002; Turanovic & Pratt, 2014). To capture risky lifestyles, we included measures of alcohol consumption, drug use, and offending behavior. A*lcohol consumption* was created using two measures about drinking behavior—the number of days the respondent reported drinking in an average month and the number of drinks they have on a typical day when they drink. We multiplied these variables to create a measure of the number of drinks the respondent consumes in an average month. Concerning *drug use*, respondents were asked whether they had ever used marijuana, powder cocaine, crack cocaine, heroin, methamphetamine, ecstasy, and illegal use of prescription drugs. If they responded positively to ever using the drug, they were asked if they used the drug in the last 12 months. We created a binary measure for any drug use in the past 12 months (1=yes; 0=no). Lastly, *offending* was also measured using multiple items of self-reported offending in the past 12 months adapted from Huizinga et al.'s (1991) Self-Reported Offending scale.[11] If the respondent answered positively to doing any of the listed offenses, they were coded as 1 and 0 if not.

Characteristics of individuals' lives that may provide structure and routine, leaving less time for riskier activities, were included to capture less-risky lifestyles (Osgood et al., 1996; see also Sampson & Laub, 1993). These included marital status and employment status. First, *marital status* was measured by asking respondents if they were currently married, not married (single), divorced, separated, widowed. We combined the four latter response categories to create a binary measure married (1) and not married (0). For *employment status*, we included several dichotomous variables— working part-time, working full-time, and retired, with not working/other serving as the reference category. Again, these measures were included to capture more structured lifestyles that would reduce engaging in risky behaviors.

Finally, measures of self-control, age, race, and gender were included in the analysis as covariates that are often associated with certain lifestyles and risk of victimization (Dugan & Apel, 2003; Hindelang et al., 1978; Lauritsen & Heimer, 2008; Lauritsen & Carbone-Lopez, 2011; Meier & Meithe, 1993; Schreck, Stewart, & Fisher, 2006; see also Mustaine & Tewksbury, 1998). The *low self-control* scale consisted of five items—1) I do certain things that are bad for me, just because they are fun, 2) pleasure and fun sometimes keep me from getting work done, 3) I am good at resisting temptation (reverse coded), 4) I often act without thinking through the alternatives, and 5) sometimes I can't stop myself from doing something, even if I know it is wrong. Response options ranged from 1 (strongly disagree)

[10]At the beginning of the survey, the field researcher defined what was meant by "block" in the survey—"When I talk about your block, I only mean [*ADDRESS* STREET NAME ONLY] *between STREET A* and *STREET B*, including both sides of your street." This definition aligns with our use of the street segment as the unit of analysis.

[11]Offenses included driving a vehicle under the influence of alcohol, damaged someone else's property on purpose, taken something that didn't belong to you, used someone else's credit card or a personal check to steal something, owned or carried a gun without a license, broken into a home or business to steal something, sold illegal drugs, stolen a car or some other type of motor vehicle, used violence against someone-like in a fist fight or assault, and taken something from someone using violence or the threat of violence.

to 4 (strongly agree). Responses were summed and averaged for each individual so that higher values represent lower levels of self-control ($\alpha = 0.705$). We also included terms for *age* (measured continuously), *race* (1=black; 0= non-black), and a *gender* (1= male; 0= female).[12]

Street-level routine activities.: The street-level measures were included to capture the three key concepts of routine activity theory—capable guardianship, suitable targets and motivated offenders. Capable guardianship consisted of four unique measures that capture the degree of guardianship or supervision provided by residents and the amount of people on the street. First, *percent retired* was created by using the employment measure from the survey and calculating the percentage of respondents that reported they were retired on each street. Second, *watch property* was based on a single item that asked respondents "how common it is for people on your block to watch each other's home property when they go away." Similarly, *prosocial use of public space* was based on an item that asked "how common is it for people your block to spend time outside for more than just a few minutes —talking with each other, reading, eating, or taking a walk." For both of these questions the response options ranged from very uncommon (1) to very common (4), and we summed and averaged this item across the completed surveys for each street for a street-level scale. Lastly, *percent walk or use public transportation* was drawn from a measure that asked respondents how they usually travel to the main places where they work, study or spend time. We then calculated the percent of respondents who reported walking or using public transportation as a measure of pedestrian flow, similar to measures of capable guardianship used by Reynald (2011) and Hollis-Peel & Welsh (2014).

To measure the presence of suitable targets we included measures that capture aspects of the street that may send cues to motivated offenders that dwelling units are easy to break into such as lacking security doors or gates or streets with vacant properties. *Percent unoccupied dwelling units* and *percent of buildings without security bars* were measures collected during physical observations on the street segments. Field researchers counted the number of dwelling units on each street, as well as which units appeared unoccupied or vacant based on a number of vacancy indicators, such as boarded up windows, eviction notices, or realtor's lock on the door. We then calculated the percent of dwelling units that were unoccupied. The field researchers also documented the number of buildings with security doors or bars on the windows on the street, so we calculated the percent of buildings *without* bars and gates.

Finally, we included two measures to reflect the presence of motivated offenders on the street. These included the percent of households with a self-reported offender and levels of social disorder on the street. *Street offender* was created using the self-reported offending measure along with a measure that asked survey respondents if they or anyone in their household was released from jail or prison in the past 12 months. We then created a binary measure of whether the street had an offender (1= yes; 0= no) based on these two measures. A social disorder scale that included eight items from the survey that were related to

[12]The sample of individuals included in the analysis departs from the full sample due to missing data at the individual level. The amount of missing data for each variable did not exceed 2% missing data, and total number of missing cases was 6.8%. Given minimal missing data, listwise deletion was used to deal with the missing data in the current analysis (see Bennett, 2001; Schafer, 1999). There were no missing data at the street level in part due to aggregating survey responses.

activity of people that may serve as motivated offenders in these places. The items included people arguing or fighting on the block, groups of kids hanging out causing problems, people drinking alcohol in public, people acting drunk or high on your block, panhandlers asking for money, people making too much noise late at night, people selling drugs outside, and prostitutes working on the block. Respondents were asked if these types of activities took place less than once a month (1), a few times a month (2), a few times a week (3), or every day (4). Mean scores were calculated for individual survey respondents (α = 0.88) that were then summed and averaged to the street-segment level. Finally, to capture commercial activity, a key land use variable related to crime and often associated with attracting offenders to the street, a measure of *percent commercial* buildings was calculated by dividing the number of buildings used for commercial purposes by the total number of buildings on the street.[13]

Community structural measures.: As previously discussed, we used census data aggregated to Community Statistical Areas to measure community characteristics. As a key exogenous, structural measure related to social disorganization and crime (Armstrong, Katz, and Schnebly 2015; Bellair 2000; Sampson, Raudenbush & Earls 1997; Velez 2001; Chant 2004), we included a measure of *concentrated disadvantage* that was comprised of percent of families living below poverty line, unemployment rate, percent female headed-households, and percent receiving public assistance (eigenvalue= 3.12; factor loadings > 0.87). Additionally, a measure of racial composition and heterogeneity (Kornhauser 1978; Sampson and Groves 1989; Velez 2001) was included using the *racial diversity index* provided by the census, and the *percent aged 19–24* was also included at the CSA level.

Descriptive statistics for all individual-, street-, and community-level variables included in the present study are provided in Table 2.[14]

Analytic Strategy—Given the nature of the data, with individuals nested within street segments nested within communities, multilevel modeling is appropriate. It allows us to examine the contribution of individual-level, street-level, and community-level covariates simultaneously and provides more accurate standard errors (Raudenbush & Bryk 2002). Level 1 of the data corresponds to characteristics of individual respondents, level 2 corresponds to measures of the street environment and routine activities on the street segments, and level 3 corresponds to the CSAs. More specifically, given the binary outcomes of victimization, we estimated multilevel logistic regression models, one for

[13]Building counts and purposes were obtained during the physical observations. Mixed-use buildings that included a commercial establishment were included in the calculation. We also obtained aggregated business and employee counts for our sample of street segments from Baltimore Neighborhood Indictors Alliance (BNIA) retrieved from InfoUSA. The number of businesses on the street was highly correlated with our measure of percent commercial (r >0.75), and there were no substantive changes in the regression models, we opted to use our direct measure consistent with the other data collected. Furthermore, we considered the role of different types of commercial establishments such as bars and liquor stores, and included a measure of whether a bar or liquor store was located on the street in different versions of the models. The direction of the variable was negative, but not significant, and there were no other substantive changes to the models, including the effect of % commercial. For parsimony, we only include the % commercial in the final models.

[14]Bivariate correlations between the independent variables (based on Pearson's r) were calculated to assess potential problems relating to multicollinearity. None of the correlations exceeded 0.5, which is below the 0.70 threshold traditionally used to identify collinearity problems (Licht, 1995). Further collinearity diagnostics were conducted to rule out the presence of harmful collinearity. Variation inflation factors among variables included in the models are below the threshold of 4 and the tolerance levels are well above 0.4, thus there is little concern for multicollinearity (see Tabachnick & Fridell, 2001).

property and another for violent victimization. Unconditional models (i.e., no covariates) were estimated for each dependent variable and between street- and community-level variance was evaluated by using the reported likelihood ratio test comparing the multilevel logistic model to a traditional logistic regression. Additionally, the proportion of variance at each level was quantified using intra class correlations.

The estimated model can be more easily conceptualized when represented as three models, one for each level (Raudenbush and Bryk 2002), as shown below:

$$\text{Individual level: } \operatorname{logit}\left\{\Pr\left(y_{ijk}=1 \middle| x_{ijk}\right)\right\} = \pi_{0jk} + \pi_{1jk}X_{1jk} + \ \ldots \ + \pi_{ijk}X_{ijk} \tag{1}$$

$$\text{Street level: } \pi_{0jk} = \beta_{00k} + \beta_{01k}Z_{01k} + \ \ldots \ + \beta_{0jk}Z_{0jk} + r_{0jk} \tag{2}$$

$$\text{Community level: } \beta_{00k} = \gamma_{000} + \gamma_{001}W_{001} + \ \ldots \ + \gamma_{00k}W_{00k} + u_{00k} \tag{3}$$

The outcome, Logit {Pr(yijk=1|x_{ijk})}, is the log-odds that $y_{ijk}=1$ given x_{ijk}, all covariates, of individual *i*, nested in street *j*, nested in community *k*. In equation (1), π_{0jk} and π_{ijk} represent the intercept and coefficient vectors for the individual-level variables, X_{ijk}. At the street level (eq. 2), π_{0jk} is modeled as a function of the street-level intercepts β_{00k}, and street-level variables, Z_{jk}, with β_{0jk} as the corresponding vector of coefficients. Lastly, in equation (3), the community-level β_{00k} is a function of community-level variables, W_{00k}, where γ_{000} is the fixed-intercept across communities, and γ_{00k} is the coefficient vector. In multilevel logistic regression the residual error term has an underlying logistic distribution with a known variance, $\sigma^2 = \frac{\pi^2}{3} \approx 3.29$ (Raudenbush & Bryk 2002), whereas the level 2 and level 3 residuals, r_{0jk} and u_{00k}, respectively, are assumed to be normally distributed. The proportion of variability at each level was then used to calculate the intra-class correlation at the street-level using equation (4) and at the community-level using equation (5).

$$\text{Level 2 ICC: } \rho_{r_0} = \frac{\tau_{r_0}^2}{\tau_{r_0}^2 + \sigma^2} \tag{4}$$

$$\text{Level 3 ICC: } \rho_{u_{00}} = \frac{\tau_{u_{00}}^2}{\tau_{r_0}^2 + \tau_{u_{00}}^2 + \sigma^2} \tag{5}$$

Results

We begin with the results from the unconditional models (i.e. no covariates) provided in Table 3. The likelihood ratio tests comparing multilevel logistic regression to traditional logistic regression was significant for both outcomes supporting the use of multilevel models. Notably, when examining the variance components and intra-class correlations in the unconditional models, violent victimization varied more across communities, rather than across streets; whereas, property victimization varied more across street segments, and less across communities. Specifically, 4.9% of the variance in individual property victimization was across street segments, compared to 2.3% of the variance was across communities. Alternatively, 10.0% of the variance in individual violent victimization was across communities and 0.2% was across street segments. These unconditional models indicate that individual risk of property and violent victimization varied significantly across street segments and communities, justifying the use of the multilevel approach.

Next, the main findings for property victimization are presented in Table 4, Model 1. At the individual-level, offending, marital status, and race were significantly related to likelihood of property victimization. Specifically, individuals who reported offending in the past year had 2.2 times greater odds (OR= exp[0.798]) of experiencing property victimization. Those who were married were also more likely to report property victimization, as were individuals who were not Black. Black individuals had 40.3% lower odds ((1- exp[−0.516]) x 100) of being victims of property crime compared to non-Blacks.

Concerning street-level measures, percent retired had a negative effect on property victimization; as percent retired increased, the odds of property victimization decreased. The prosocial use of public space and percent of residents who walk or use public transportation also decreased the likelihood of property victimization. More specifically, a one-point increase in the prosocial use of public space scale decreased the odds of property victimization by 32.7% ((1- exp[−0.397]) x 100). Alternatively, the percent of unoccupied dwelling units and social disorder had a positive effect, increasing the likelihood of experiencing property victimization as the amount of vacancies and social disorder on the street rises. Finally, a greater amount of commercial buildings on the street decreased risk of reported residential property victimization—a percentage point increase in percent commercial lowers the odds of property victimization by 1.6% ((1- exp[−0.016]) x 100). In regard to the community-level measures, none of them had a statistically significant relationship with property victimization.

The results for violent victimization are presented in Table 4, Model 2. Since there was little level 2 variance to explain (0.2%), the inclusion of individual-level covariates explained all between-street variance, therefore, the resulting multilevel model is a two-level logistic regression with individuals at level 1 nested in communities at level 2.[15] Similar to property victimization, offending was a strong predictor of violent victimization; individuals who reported offending in the past year had 2.68 times higher odds (OR = exp[0.986]) of experiencing violent victimization in the prior year. Being employed had a negative effect on victimization where individuals who worked had 58.8% lower odds ((1- exp[−0.888]) x 100) of being victimized. In regard to demographic characteristics, being Black and male

[15]The results from the three-level model did not vary substantively, nor did a penalized logistic regression without accounting for nesting; therefore, we report the 2-level multilevel model most appropriate for the nested structure of the data. Covariates at the street-level are still included as they can have an impact on the individual-level outcome, but the variables explain individual-level variance, not street.

both had a negative effect on violent victimization. Blacks had 48.7% lower odds ((1- exp[−0.667]) x 100) of experiencing violent victimization compared to non-Blacks, and males had 37.1% lower odds ((1- exp[−0.464]) x 100) of being violently victimized, when controlling for the other covariates.

At the street-segment level, social disorder was the only significant variable for violent victimization, increasing the odds of experiencing violent victimization. Differing from the findings of property victimization, though consistent with prior research, community concentrated disadvantage and racial diversity increased the likelihood of violent victimization.

Given the sampling design focused on different types of street segments and overrepresentation of crime hot spots, we ran additional models controlling for the street segment type. Results are provided in Appendix A, but it is noteworthy that the segment type is not significant and there are no substantive changes in the main results. Sensitivity analyses using census tracts rather than CSAs are again similar, with two main differences in the violent victimization model and one difference in the property victimization model. The effect of gender at level 1 and concentrated disadvantage at level 3 on violent victimization both become not significant, and percent commercial buildings at level 2 is not significantly related to property victimization. The results from these models are provided in Appendix B.

Discussion

The current study sought to address key gaps in research on victimization by including the microgeographic context of streets people live on, and examining violent and property victimization that occurred on their street, while also accounting for individual characteristics and the broader community context. Residential street segments can be viewed as small-scale communities where residents develop roles and engage in activities that impact opportunity structures of the street, but due to data limitations, prior research has been limited in its ability to capture the informal nature of routines on residential streets and how levels of guardianship, suitable targets and motivated offenders influence the risk of victimization *on the street*. Our findings reinforce earlier research, but also provide new insights on the role of microgeographic places on victimization that warrant further discussion.

First, our study confirms prior research that emphasizes the importance of the risky lifestyles perspective when applied to street segments. In particular, our study reinforces the importance of the victim/offender overlap with individuals who reported offending in the past year being significantly more likely to be victims of both violent and property crime (Armstrong & Griffin, 2007; Berg et al., 2012; Jennings, Piquero & Reingle, 2012; Lauritsen et al., 1991; Sampson & Lauritsen, 1990; Schreck et al., 2008). Individuals involved in crime often associate with other individuals involved in criminal behavior increasing their own exposure to motivated offenders (Turanovic & Pratt, 2014), as well as being viewed as an easier target because they may be less likely to go to the police when victimized if their own offending may have contributed to the victimization (Siegel, 1985; Sparks, 1982). Reflecting a more structured, less risky lifestyle, individuals who were employed full-time were less likely to experience violent victimization on the street. Being employed is typically a structured, prosocial activity that takes up a great deal of free time, resulting in fewer opportunities for contact with offenders or engaging in unstructured activities such as drinking at bars, thus reducing the risk of victimization (see Osgood et al., 1996). Additionally, if one is employed they are likely spending less time on the street they live on or in the home, thus employment reduces the likelihood experiencing victimization on the street. In regard to property victimization, individual factors were less prominent for understanding street level victimization, which makes sense given that property crime is tied more to characteristics of the place than the person, which will be discussed shortly.

Second, our study supports prior research on crime in communities that structural measures of communities are important antecedents for violent crime and victimization, even when accounting for the street segment environment. Following social disorganization theory, concentrated disadvantage at the community level, along with racial diversity, was associated with a significant increase in the likelihood of violent victimization that occurred on the street. Importantly, the small proportion of variation in violent victimization at the street segment level, suggests that the street context plays a lesser role in experiencing violent victimization relative to the broader community. Alternatively, community characteristics did not have a significant role in explaining residential property victimization and the street segment was a more important context for experiencing property victimization.

Third, and a key contribution of the current study, is the role of the street-level environment on victimization occurring on the street, particularly for property victimization. The ability to examine victimization at a micro-geographic level has been limited due to lack of self-report data at the street-segment level. First, social disorder was significantly associated with higher likelihood of property victimization, and was the only significant street-level variable for violent victimization (see also Jones & Pridemore, 2019). The level of people engaging in forms of social disorder— being drunk or high in public, groups of kids hanging out causing problems, people arguing or fighting on the block, may represent aspects of the motivated offender component in routine activity and the breakdown of informal social controls according the social disorganization theory. This is noteworthy because scholars have traditionally argued that social disorganization and collective efficacy operate primarily at the community level (Braga & Clarke, 2017, Wilcox et al., 2007; Wikstrom et al. 2012), but the current study aligns with more recent research that suggests these concepts also operate at the street-level (Jones & Pridemore, 2019; Weisburd et al., 2014; Weisburd et al., 2020; 2021).

However, our findings regarding the relative salience of opportunity theories for understanding property crime victimization is more important. A series of street-level measures used to capture opportunity structures such as levels of guardianship, suitable targets, and motivated offenders played an essential role in the likelihood of property victimization on the street. Whether measured by the percent walking and using public transportation, the percent of retired resident, or the level of prosocial activity on the street, the general presence of individuals at home or on the street using public space provided guardianship against property victimization. Offenders interested in stealing property or breaking into someone's home may be deterred when people are present on the street walking or waiting for the bus, spending time chatting with their neighbors or simply at home. In regard to opportunity related to suitable targets, unoccupied dwelling units on the street increased the risk of property victimization. Vacant dwelling units may signal target suitability as the units are left unattended and possibly abandoned with goods left behind. Unoccupied dwelling units may also represent a lack of capable guardianship, particularly on streets where there are more homes unattended than not, serving as a place for offenders to spend time without being detected (Boessen & Hipp, 2015). As broken windows theory would suggest, vacancy and the associated characteristics such as unkempt yards with overgrown weeds and shrubs provide places to hide and obstruct visibility from the street. Furthermore, it may send a signal to outsiders that residents do not care about the place and are unlikely to intervene if someone commits a crime, and this environment may turn a simple passerby into a motivated offender (Sampson & Raudenbush, 1999; Skogan, 1990).

Percent commercial buildings provided a protective element against property victimization, which we believe suggests the importance of crime opportunities in understanding property crime victimization. While commercial activity is thought to increase opportunities for crime (i.e. crime generators) due to the presence of suitable targets (i.e. shoppers) visiting businesses and attracting motivated offenders to the area (Brantingham & Brantingham, 1995; Browning et al., 2010; Browning, et al., 2017; Sohn, 2016; see also Zahnow, 2018), we found that commercial establishments did not affect violent victimization nor did it increase opportunities for residential property victimization. Commercial buildings may have more security that provides guardianship on the street influencing the overall suitability of individuals as targets, as well as the prevalence of residential units to target. Certainly, offenders consider the neighborhood where specific types of places are located, but the decision to offend likely comes from the opportunity in the direct environment of the street. Therefore, the criminogenic effect of commercial activity may occur at larger spatial units; that is, people carrying money and goods may experience victimization *coming and going* to the commercial area, but not on the street where businesses are located, where they provide guardianship.

Our study accordingly extends existing research in this area by identifying that risky lifestyles and social disorganization are key factors in understanding victimization at the street segment level. It also supports opportunity theorists who emphasize crime opportunities at the local level, at least for property crime victimization on the street. But findings regarding Blacks and males raise additional questions not answered necessarily by the existing literature. We find that when residents were Black or males they were less likely to experience violent crime victimization at the street segment level, and Blacks were less likely to have experienced property crime victimization. We note that in both cases the results are not due to instability in the models created by multi-collinearity. In each of these cases, the hierarchical multivariate findings follow simple zero order correlations. We suspect that our findings regarding gender represent the particular vulnerability of women to violence in the home, as 74% of the victims of the violent victimizations that occurred in the home (n=38) were female. We explored further limiting the dependent variable to only those victimizations that occurred on the street (n=68), and the effect of gender did not change, with females more likely to experience violence on the street as well. Research should consider how the street environment may have different and indirect impacts on violence experiences for males and females, as well as in the home versus on the street. It may be that males are more at risk for victimization further from their residence compared to females.

Explaining the outcomes regarding race is also difficult. We suspect that race here may reflect social advantage that might make whites more vulnerable to victimization, especially in a city where hot spots of crime are interspersed across the city. Additionally, our sample of respondents is older and does not include those under 21, therefore we do not capture those at higher risk of violent victimization—*young, black males*. Irrespective, this is something for future research to investigate to identify whether the findings are specific to Baltimore or represent more general trends.

The findings from the current study have additional implications for theory and policy. The use of original, primary data collected at the street-segment level using residential surveys and direct physical observations of the street allowed us to think creatively about aspects of opportunity and routine activities, and operationalize key theoretical constructs with unique measures that previous research has been unable to develop. For instance, Jones and Pridemore (2019) used official measures of local guardianship such as police stations, fire stations, security alarms and cameras, and note that "guardianship remains one of the most difficult aspects of opportunity theory to operationalize" (p. 565). We argue that our measures attempt to address this criticism and capture the more informal ways residents provide guardianship on the street. Our measures of routine activities still reinforce and support existing literature, which validates the use of secondary data that are more accessible to serve as proxy measures of street environment until more data collected on streets is available. Future research should further attempt to collect data at the microgeographic level to more directly measure the movement and routine activities of small places, and examine the extent to which the nature of someone's street reduces or increases risk of victimization and why. Researchers recognize the multi-level nature of "communities" from the microgeographic level to the broad, macrogeographic (see Jones & Pridemore, 2019; Wilcox, et al., 2003), and they matter in different ways, but we need additional research on the mechanisms that operate at different levels.

In addition to these theoretical implications, there are also policy implications worth noting. The importance of addressing levels of social disorder, vacant lots and unoccupied dwelling units, as well as encouraging prosocial use of public space might be modifiable factors that could subsequently reduce risk of property victimization. Research has found that place-based strategies at crime hot spots are effective crime prevention programs in reducing crime and disorder, compared to those deployed in broad community areas (Sherman & Weisburd, 1995; Braga, Papachristos, & Hureau, 2014). The fact that we found that residents who are home and use public spaces, as well as people on the street (riding public transportation or walking) provide a protective element and suggests that informal aspects of guardianship can protect against property victimization. Programs that provide formal guardianship such as police foot patrols or random visits to crime hot spots may be effective, but our findings suggest that programs that focus on encouraging residents to use public space for prosocial activities, may negate the risks associated with general street activity. With the exception of the effect of social disorder in these places on violent victimization, our study suggests that such targeted efforts at the street-level may not have as great an impact on violent victimization. On the other hand, prevention of violent victimization may still largely operate at the individual level with efforts focused at altering individual lifestyles and risk factors, as well as the community context and concentrated disadvantage that is associated with violence.

Limitations

While the current study allowed us to examine routine activities at a different ecological unit, the prospects for future research to consider the role of microgeographic places on victimization are plentiful. First, we operationalized new measures of routine activities at the street segment that need further testing, and we did not have direct measures of how individuals spend their time, such as shopping, going to bars, or the commonly used measure of how many evenings one spends spend away from the home. Instead, we have measures of structured activities such as being employed that likely influence engaging in risky behaviors. While our measures do include risky behaviors such as offending and substance use, which are validated in research, future research should incorporate measures that capture the nuances of lifestyles such as with whom, how much, and in what context risky behaviors are taking place (Dong, Branas, Richmond, Morrison, & Wiebe, 2017). Again, future research should further consider the multilevel complexities of the various contexts that can influence victimization risk, particularly violent victimization given the relative rareness of violent victimization. We had a small number of violent victimizations in the sample, even more so when limited to only those that took place on the street and not inside the home, highlighting the low rates of violent victimization overall in the sample, even given a sample composed predominately of hot spots. We also note that our study is cross-sectional, so we are limited in the ability to make causal statements about lifestyles, opportunity and victimization; the time-ordering of some measures, such as offending, where victimization can arguably lead to engaging in illegal behavior, as the overlap in offending/victimization and causal order is difficult to tease apart (see Turanovic & Pratt, 2014). Victimization may also lead to less use of public space and public transportation or walking, but again, time-ordering is not assessed in the current study. Finally, our unique sampling strategy focused on Baltimore and more specifically residential streets in Baltimore, not representing victimization that occurs in business and commercial areas, such as the Inner Harbor or streets near sports stadiums, and limiting our ability to generalize findings to other places.

Conclusions

This is the first study we are aware of that allowed us to examine the role of individual characteristics, the microgeographic context, and structural factors of the community on victimization simultaneously in studying street level victimization. Following prior research, our study shows that risky lifestyles play a key role in understanding both property and violent crime victimization, and that community indicators of disadvantage play a role in explaining victimization. A key contribution of our study was to show that the immediate situational environment of the street segment must be taken into account if we are to fully understand property and violent crime victimization. We found that the importance of the micro geographic environment varied, with property crime victimization being much more broadly impacted than violent crime. Opportunity variables at the street segment level are most salient for understanding property crime victimization. In contrast, social disorganization at the street segment is related to both property crime and violent crime. We think these conclusions provide insight not only into the ways in which individual, street, and community characteristics influence crime, but also point to the fact that crime prevention strategies should consider each level in developing prevention programs.

Appendix

Appendix

Appendix A.

Three-level Random Intercept Mixed Model with Street Segment Type

	Model 1			Model 2		
	Property Victimization			Violent Victimization		
	b	SE	exp(b)	b	SE	exp(b)
Fixed Effects						
Intercept	−1.329	0.656	--	−4.733**	1.547	--
Individual-level variables						
Drinking	0.000	0.002	1.000	0.008	0.005	1.008
Illicit drug use	0.053	0.112	1.054	0.034	0.263	1.035
Offending	0.796***	0.131	2.217	0.983***	0.280	2.672
Employed part-time	−0.074	0.141	0.929	−0.342	0.328	0.710
Employed full-time	0.112	0.103	1.119	−0.904**	0.289	0.405
Retired	−0.181	0.180	0.834	−0.027	0.478	0.973
Married	0.231*	0.104	1.260	0.427	0.268	1.533
Low self-control	−0.069	0.105	0.933	0.382	0.260	1.465
Age	0.001	0.003	1.001	−0.011	0.009	0.989
Black	−0.518***	0.111	0.596	−0.654**	0.253	0.520
Male	−0.176	0.090	0.839	−0.473*	0.237	0.623
Street-level variables						
Capable Guardianship						
Percent retired	−0.012**	0.004	0.988	−0.009	0.012	0.991
Watch property	0.156	0.140	1.169	0.059	0.335	1.061
Prosocial use of public space	−0.390**	0.156	0.677	−0.068	0.388	0.934
Percent walk or use public transportation	−0.011***	0.003	0.989	0.008	0.006	1.008
Suitable Targets						
Unoccupied dwelling units	0.009*	0.004	1.009	−0.000	0.011	1.000
Percent of buildings without security bars	0.000	0.002	1.000	−0.002	0.006	0.998
Motivated Offenders						
Street offender	−0.060	0.109	0.942	0.307	0.310	1.359
Social disorder	0.592***	0.129	1.808	0.607*	0.286	1.835

	Model 1			**Model 2**		
	Property Victimization			**Violent Victimization**		
	b	**SE**	**exp(b)**	**b**	**SE**	**exp(b)**
Percent commercial	−0.017**	0.006	0.983	0.005	0.011	1.005
Segment type (reference group- cold street)						
Cool	0.006	0.175	1.006	−0.514	0.527	0.598
Drug	−0.035	0.194	0.966	−0.201	0.517	0.818
Violent	−0.019	0.187	0.981	−0.208	0.497	0.812
Combined drug/violent	−0.306	0.229	0.736	−0.404	0.572	0.668
Community-level variables						
Concentrated disadvantage	0.126	0.085	1.134	0.408*	0.201	1.504
Racial diversity	0.002	0.003	1.002	0.020*	0.007	1.020
% Aged 19–24	0.010	0.012	1.010	−0.037	0.030	0.964
Random Effects						
τ^2_{r0}	0.033			0.000		
τ^2_{u00}	0.040			0.008		
χ^2	4.15			0.01		
−2 Log Likelihood	3,478.00			758.73		

Note.

* $p \leq .05$,

** $p \leq .01$,

*** $p \leq .001$

N = 3,473 individuals (level 1); N = 449 streets (level 2); N=53 communities (level 3)

Appendix

Appendix B.

Census Tract, Three-level Random Intercept Mixed Model of Property and Violent Victimization (Individuals nested in streets, nested in census tracts)

	Model 1			**Model 2**		
	Property Victimization			**Violent Victimization**		
	b	**SE**	**exp(b)**	**b**	**SE**	**exp(b)**
Fixed Effects						
Intercept	−0.844	0.700	--	−5.282	1.892	
Individual-level variables						
Drinking	−0.001	0.003	0.999	0.008	0.005	1.008
Illicit drug use	0.011	0.118	1.011	−0.044	0.283	0.957
Offending	0.786***	0.138	2.195	1.045***	0.273	2.843

	Model 1			Model 2		
	Property Victimization			Violent Victimization		
	b	**SE**	**exp(b)**	**b**	**SE**	**exp(b)**
Employed part-time	−0.106	0.149	0.899	−0.345	0.343	0.708
Employed full-time	0.079	0.109	1.082	−0.883**	0.315	0.414
Retired	−0.247	0.192	0.781	−0.332	0.529	0.717
Married	0.258*	0.110	1.294	0.377	0.274	1.458
Low self-control	−0.119	0.110	0.888	0.344	0.295	1.411
Age	0.000	0.004	1.000	−0.006	0.009	0.994
Black	−0.465***	0.117	0.628	−0.719**	0.259	0.487
Male	−0.174	0.096	0.840	−0.397	0.261	0.672
Street-level variables						
Capable Guardianship						
Percent retired	−0.009*	0.004	0.991	−0.003	0.012	0.997
Watch property	0.231	0.152	1.260	0.128	0.348	1.137
Prosocial use of public space	−0.480**	0.167	0.619	−0.119	0.453	0.888
Percent walk or use public transportation	−0.009***	0.003	0.991	0.009	0.007	1.009
Suitable Targets						
Unoccupied dwelling units	0.011*	0.005	1.011	−0.011	0.012	0.989
Percent of buildings without security bars	−0.002	0.002	0.998	−0.004	0.006	0.996
Motivated Offenders						
Street offender	0.041	0.118	1.042	0.396	0.357	1.486
Social disorder	0.533***	0.123	1.704	0.855***	0.249	2.351
Percent commercial	−0.015	0.008	0.985	−0.008	0.012	0.992
Community-level variables						
Concentrated disadvantage	0.090	0.067	1.094	0.179	0.135	1.196
Racial diversity	0.002	0.003	1.002	0.013*	0.006	1.013
% Aged 18–24	−0.530	1.291	0.589	−1.588	3.739	0.204
Random Effects						
τ_{r0}^2		0.086			--	
τ_{u00}^2		0.000			--	
χ^2		6.00**			--	
−2 Log Likelihood		3,105.206			667.501	

Note.

*$p \leq .05$,

**$p \leq .01$,

***$p \leq .001$

N = 3,107 individuals (level 1); N = 400 streets (level 2); N=150 Census tracts (level 3).

In the process of nesting the street segments in the census tracts (spatial join), there were a number of issues that arose and should be acknowledged. Baltimore city has 200 census tracts, 50 census tracts were not represented because there were no sampled street segments from these census tracts. Furthermore, there are 49 census tracts that had only one street segment.

Additionally, 49 street segments were located on borders of census tracts and could not be assigned a census tract, so they were removed from these analyses. When the unconditional multilevel models were estimated, there was not significant variation in the violent victimization outcome across census tracts, therefor the violent victimization model is a logistic regression with robust standard errors.

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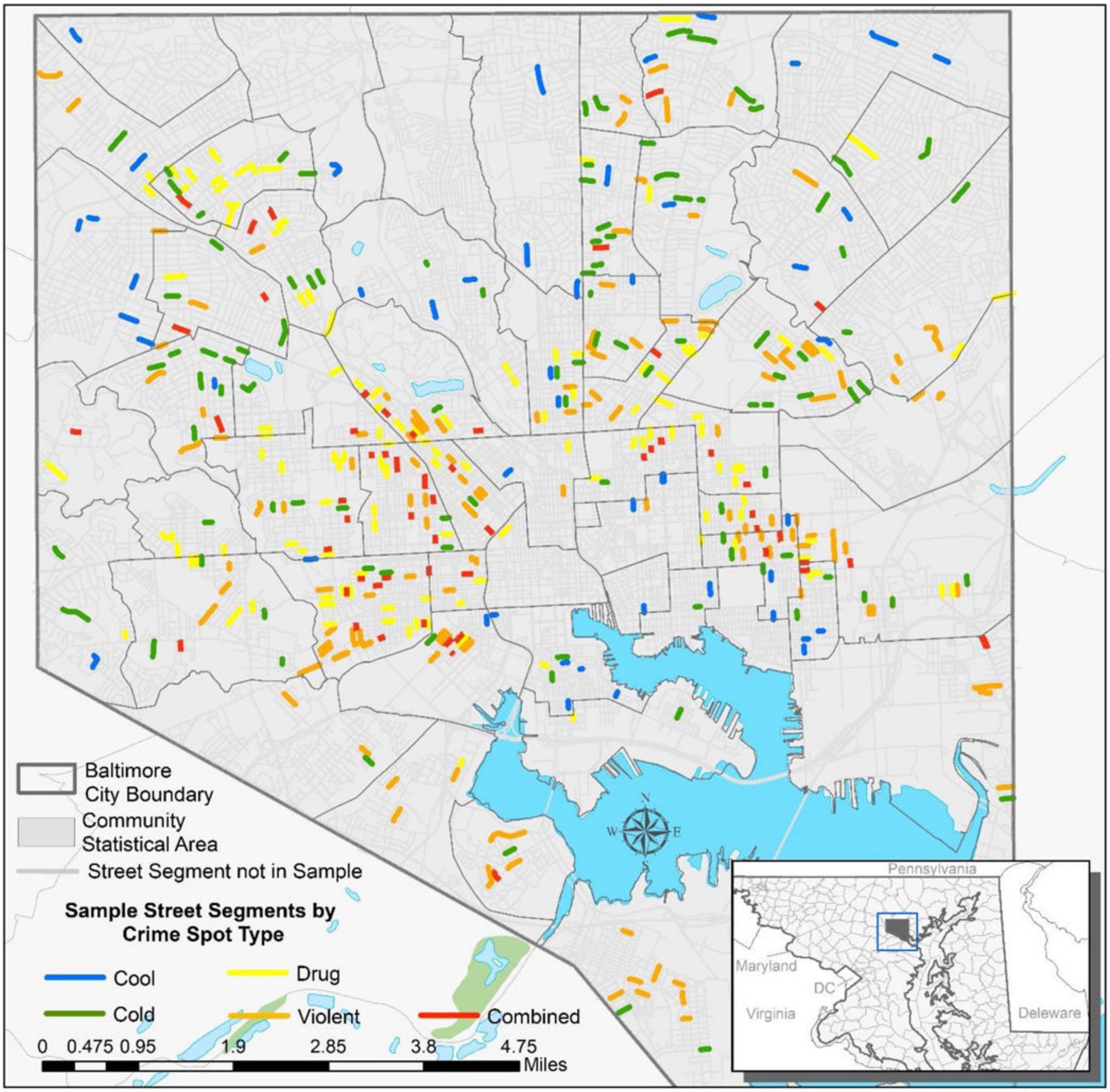

Figure 1.
Study Sample Street Segments by Crime Type in Baltimore City, Maryland

Table 1.

Mean (standard deviation) of Crime Calls in Sampled Street Segments

Type of Street Segment	N	Violent Crime	Drug Crime	Other Crime and Disorder
Cold Spot	47	1.45 (1.04)	0.19 (0.45)	15.72 (8.67)
Cool Spot	100	6.30 (3.59)	2.86 (3.28)	33.10 (15.58)
Drug Spot	121	10.05 (4.36)	34.03 (21.58)	65.45 (27.77)
Violent Spot	126	25.43 (9.99)	6.45 (4.73)	88.33 (45.30)
Combined Spot	55	31.24 (12.76)	74.75 (157.56)	145.27 (112.98)

Table 2.

Descriptive Statistics

	Mean (SD) or %	Range
Individual-level data (n=3,491)		
Dependent Variables		
Property victimization (in past year)	21.63%	0 – 1
Violent victimization (in past year)	2.68%	0 – 1
Independent Variables		
Alcohol consumption	9.34 (18.66)	0 – 90
Drug use	0.226	0 – 1
Offending	0.116	0 – 1
Employment status		0 – 1
Not working/other (reference category)	0.382	0 – 1
Part-time	0.129	0 – 1
Full-time	0.364	0 – 1
Retired	0.125	0 – 1
Marital status (married)	0.228	0 – 1
Low self-control	2.08 (0.42)	1 – 4
Age	44.49 (15.67)	21 – 95
Race (black)	0.751	0 – 1
Gender (male)	0.418	0 – 1
Street-level data (n=449)		
Capable Guardianship		
Percent retired	12.74 (13.07)	0 – 62.5
Watch property	3.08 (0.38)	2 – 3.88
Prosocial use of public space	3.16 (0.34)	2.14 – 4.00
Percent walk or use public transportation	45.64 (23.03)	0 – 100
Suitable Targets		
Percent of unoccupied dwelling units	11.29 (12.08)	0 – 65.9
Percent of buildings without security bars	66.62 (22.14)	0 – 100
Motivated Offenders		
Street offender	72.38	0 – 1
Social disorder	1.70 (0.49)	1 – 3.22
Percent commercial buildings	3.58 (9.09)	0 – 91.30
Community-level data (n=53)		
Concentrated disadvantage factor	0.06 (0.96)	−1.55 – 2.03
% Female-headed households	54.01 (16.98)	15.09 – 81.43
% Families living below poverty	20.86 (12.02)	3.51 – 52.19
Unemployment rate	15.31 (6.70)	4.27 – 30.11
% Families receiving public assistance	10.51 (7.76)	0.17 – 29.09
Racial diversity index	36.53 (22.58)	7.33 – 77.77
% Aged 19–24	12.06 (5.00)	4.2 – 33.87

Table 3.

Unconditional Three-level Random Intercept Mixed Model of Property and Violent Victimization

	Model 1		Model 2	
	Property Victimization		Violent Victimization	
	b	SE	b	SE
Fixed Effects				
Intercept	−1.383***	0.067	−3.819***	0.209
Random Effects				
Level 2 (street) Variance τ_{r0}^2	0.173		0.007	
Level 3 (community) Variance τ_{u00}^2	0.081		0.367	
Street ICC	0.049		0.002	
Community ICC	0.023		0.100	
χ^2	26.82***		11.46**	
−2 Log Likelihood	3,850.612		909.902	

Note.

* $p \leq .05$,

** $p \leq .01$,

*** $p \leq .001$

N = 3,473 individuals (level 1); N = 449 streets (level 2); N=53 communities (level 3)

Table 4.

Three-level Random Intercept Mixed Model of Property and Violent Victimization

	Model 1			Model 2		
	Property Victimization			Violent Victimization		
	b	SE	exp(b)	b	SE	exp(b)
Fixed Effects						
Intercept	−1.296	0.650	--	−4.997**	1.535	--
Individual-level variables						
Drinking	0.000	0.002	1.000	0.008	0.005	1.008
Illicit drug use	0.049	0.112	1.050	0.017	0.263	1.017
Offending	0.798***	0.131	2.221	0.986***	0.279	2.680
Employed part-time	−0.074	0.141	0.929	−0.333	0.327	0.717
Employed full-time	0.116	0.103	1.123	−0.888**	0.287	0.412
Retired	−0.179	0.180	0.836	−0.009	0.478	0.991
Married	0.227*	0.104	1.255	0.414	0.267	1.513
Low self-control	−0.070	0.105	0.933	0.392	0.261	1.480
Age	0.001	0.004	1.001	−0.011	0.009	0.989
Black	−0.516***	0.111	0.597	−0.667**	0.252	0.513
Male	−0.176	0.090	0.838	−0.464*	0.237	0.629
Street-level variables						
Capable Guardianship						
Percent retired	−0.009**	0.004	0.991	−0.009	0.012	0.991
Watch property	0.159	0.140	1.173	0.035	0.329	1.036
Prosocial use of public space	−0.397*	0.156	0.673	−0.040	0.384	0.961
Percent walk or use public transportation	−0.011***	0.002	0.989	0.007	0.006	1.007
Suitable Targets						
Unoccupied dwelling units	0.009*	0.004	1.010	−0.001	0.011	1.000
Percent of buildings without security bars	−0.0004	0.002	1.000	−0.003	0.006	0.997
Motivated Offenders						
Street offender	−0.061	0.109	0.955	0.287	0.309	1.332
Social disorder	0.551***	0.118	1.735	0.593*	0.260	1.809
Percent commercial	−0.016*	0.006	0.984	0.005	0.011	1.005
Community-level variables						
Concentrated disadvantage	0.129	0.084	1.138	0.417*	0.197	1.518
Racial diversity	0.002	0.003	1.002	0.020***	0.006	1.021
% Aged 19–24	0.010	0.012	1.010	−0.035	0.030	0.966
Random Effects						
$\tau_{r_0}^2$	0.040			--		

	Model 1			Model 2		
	Property Victimization			Violent Victimization		
	b	SE	exp(b)	b	SE	exp(b)
τ^2_{u00}		0.041			0.007	
χ^2		4.44			0.000	
−2 Log Likelihood		3,482.19			760.21	

Note.

* $p \leq .05$,

** $p \leq .01$,

*** $p \leq .001$

N = 3,505 individuals (level 1); *N* = 449 streets (level 2); N=53 communities (level 3).