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DOES COLLECTIVE EFFICACY MATTER AT THE MICRO GEOGRAPHIC LEVEL?: FINDINGS FROM A STUDY OF STREET SEGMENTS

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Many scholars argue that collective efficacy is not relevant to understanding crime at the microgeographic level. We examine variation in collective efficacy across streets with different levels of crime in Baltimore City, MD, and, then, employ multilevel modelling to assess this relationship. We find that people who live in crime hot spots have much lower levels of collective efficacy than people who live in non-hot spot streets and that this relationship persists when controlling for a large number of potential confounders both at the street and community levels. These findings suggest the importance of collective efficacy both in understanding and controlling crime at microgeographic units.

Key Words: collective efficacy, crime hot spots, crime and place, street segments, Baltimore

The relationship between informal social control and crime has been a key part of criminological research since sociologists of the Chicago School coined the term 'social disorganization' in the 1920s to represent the degree to which neighbourhoods were unable to exercise informal social control to prevent crime (Burgess 1925; Park and Burgess 1925; Shaw *et al.* 1929; Shaw and McKay 1942). Importantly, such failures of social organization were seen to be the result of the heterogeneity of populations, residential turnover and poverty and related social disadvantage found in specific urban neighbourhoods in the city (Shaw and McKay 1942; Sampson and Groves 1989; Warner and Pierce 1993; Bellair 1997; Warner and Rountree 1997; Silver and Miller 2004; Hipp 2007). In such areas, social ties are weak and residents do not invest in relationships necessary for informal social control and self-regulation, resulting in the presence of high crime rates (Kasarda and Janowitz 1974; Kornhauser 1978; Bursik and Grasmick 1993).

In recent years, researchers have emphasized intervening mechanisms of social disorganization in understanding crime in cities. Sampson *et al.* (1997) e.g. extended the concept of social disorganization to emphasize the capacity of a neighbourhood to realize common values and regulate behaviour through cohesive relationships and mutual trust among residents (see also Sampson 2012). They coined the term 'collective efficacy' or the 'willingness [of residents] to intervene for the common good' to emphasize the mechanisms by which a community can prevent crime (Sampson *et al.* 1997: 919). Key to this perspective is the idea of 'delinquency areas' or communities that have consistently high

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crime levels regardless of changing demographics (Shaw 1929). Collective efficacy and social disorganization more generally are seen to operate at a broad-area level.

Over the last two decades, however, scholars have begun to identify significant variability of crime within communities or neighbourhoods (e.g. see Groff *et al.* 2010; Hipp 2010;Tita and Radil 2010; Weisburd *et al.* 2012; Taylor 2015; Steenbeek and Weisburd 2016; Schnell *et al.* 2017). Beginning in the late 1980s, a series of studies have shown that a very large proportion of crime occurs at a small proportion of addresses, street segments or clusters of street segments (e.g. see Pierce *et al.* 1988; Sherman *et al.* 1989; Weisburd *et al.* 1992; Weisburd and Green 1995; Brantingham and Brantingham 1999; Roncek 2000; Weisburd *et al.* 2004; Weisburd *et al.* 2009; Andresen and Malleson 2011; Andresen and Linning 2012). Importantly, such high-crime streets are spread across the city and, even in communities that are seen as high-crime areas, most streets have little or no crime (Weisburd *et al.* 2012).

This has led some scholars to challenge the importance of social disorganization and collective efficacy theory for understanding crime within communities (e.g. see Sherman 1987; Braga and Clark 2014; Schnell *et al.* 2017). Simply stated, if crime is highly concentrated at crime hot spots, and such hot spots are spread across the city landscape, then a theoretical perspective that relies on the concept of delinquency areas or socially disorganized communities cannot explain why crime is concentrated at specific microgeographic hot spots. As Braga and Clarke (2014: 489) note, it is more 'appropriate to articulate the potential for informal social control by the more straightforward concepts of guardianship and effective place management drawn from opportunity theories of crime'.

In this paper, we capitalize on a survey of 3,738 individuals who were sampled from 449 street segments with varying rates of drug and violent crime in Baltimore City, MD. We examine two main research questions in our study. First, does self-reported collective efficacy vary by types of hot spot and non-hot spot street segments? If collective efficacy is relevant to understanding crime at the microgeographic level, we would expect lower levels of collective efficacy on streets that are crime hot spots. Second, does the relationship between collective efficacy and crime at street segments remain salient once relevant street-level covariates and community structural indicators of collective efficacy are taken into account? We use multilevel modelling to account for the nesting of streets within neighbourhoods and control for a series of street-level and community-level confounders to examine this question.

Collective Efficacy and Microgeographic Communities

In a seminal revision of social disorganization theory, Sampson *et al.* (1997) extended the concept of social control to emphasize the capacity of a community to realize common values and regulate behaviour through cohesive relationships and mutual trust among residents (see also Sampson 2006; 2012). Collective efficacy was conceptualized as the willingness of neighbourhood residents to take action and intervene, which relied on mutual trust among residents (Sampson *et al.* 2002; Kubrin and Weitzer 2003). Collective efficacy was measured by combining two scales, one of willingness to intervene (also termed 'informal social control') and the other of social cohesion and trust. Sampson *et al.* (1997) hypothesized that collective efficacy would mediate the relationship between structural characteristics and neighbourhood crime rates. In this context, concentrated disadvantage and residential instability would lower collective efficacy in the community, which, in turn, would increase crime rates.

But scholars who have explored crime at the microgeographic level have come to argue that the concept of collective efficacy has little salience for understanding the concentration of crime at specific streets in a city. Sherman *et al.* e.g. who first introduced the idea of a 'criminology of place' noted: 'Traditional collectivity theories [termed here as social disorganization theories] may be appropriate for explaining community-level variation, but they seem inappropriate for small, publicly visible places with highly transient populations' (Sherman *et al.* 1989: 30). More recently, Braga and Clarke (2014; see also Schnell 2017) also argued that the mechanisms of collective efficacy do not operate at the microgeographic level. They suggested that the application of collective efficacy to microgeographic places such as street segments goes beyond the original domain of social disorganization theory. Collective efficacy in their view is an area-level concept, much as social disorganization was linked to 'delinquency areas' (Shaw 1929). In this context, it does not make sense to apply the theory to the variability that has been observed within communities.

> It is unclear whether the community-level concept of collective efficacy can adequately explain why a particular crime spot is persistently hot over time. It is always dangerous to extend the application of theory (in this case, collective efficacy) beyond its intended domain (in this case, neighborhoods) (Braga and Clarke 2014: 497–498).

Some scholars have sought to integrate opportunity and social disorganization theories at place, though these scholars generally attribute the influence of social disorganization theory to higher-level mesogeographic and macrogeographic units, while attributing the influence of microgeographic places to opportunity theories (e.g. see Wilcox *et al.* 2003; 2007; Wikström *et al.* 2012; Bannister *et al.* 2019; Wilcox and Tillyer 2018). Wilcox, Tillyer and colleagues e.g. proposed an explicit 'place in neighborhood' theory to integrate community-level and place-level theories that emphasizes the 'multilevel approach to understanding crime places in neighborhood context' (Wilcox and Tillyer 2018: 132; also see Wilcox *et al.* 2003). The role of informal social control, however, remains a macrolevel process affecting the 'market contexts for crime' (Wilcox and Tillyer 2018: 132). In 'well-controlled contexts' or socially organized neighbourhoods, the effort and reward of offending are lessened as place-level risk is increased by market risk (Wilcox and Tillyer 2018: 133). That is, crime is less likely to occur in these places because of heightened levels of social control at the neighbourhood level.

Is collective efficacy relevant for understanding the variability of crime at microgeographic units such as street segments? Weisburd *et al.* (2012; see also Weisburd *et al.* 2014; 2017) argue that street segments do not simply represent physical entities but that they are also social settings or, following Wicker (1987: 614), 'behaviour settings' that can be seen as 'small-scale social systems' or small-scale communities (see Taylor 1997). People who frequent a street segment get to know one another and become familiar with each other's routines. Residents develop certain roles they play in the life of the street segment (e.g. the busybody, the dog watcher and the organizer). Norms about acceptable behaviour develop and are generally shared. Blocks have standing patterns of behaviour, e.g. people whose routines are regular like the mail carrier or the local shop owner. In this context, we can see street segments as 'microcommunities' as well as 'microplaces'. They have many of the traits of communities that have been seen as crucial to social disorganization theory in that these physical units function also as social units with specific norms and routines. In turn, if microgeographic units such as street segments can be seen as a type of 'microcommunity', then collective efficacy should have direct relevance to our understanding of the level of crime on street segments.

Braga and Clarke (2014; 2017) note that even if measures of street-level collective efficacy can be used to explain crime, measures in studies, to date, are proxy measures and, therefore, fail to capture the concept directly. Weisburd *et al.* (2012; 2014) measured collective efficacy on street segments by assessing the proportion of active voters on a street (as indicated by voting patterns over a two-year period). They found that it significantly influenced crime. While voting once does not necessarily show a strong commitment to involvement in public affairs, Weisburd *et al.* (2014) argued that voting consistently over time says more about an individual's commitment to social issues (see Putnam 2000; Coleman 2005). It reflects a general propensity towards civic engagement that is likely to be even stronger on their home street segment. Irrespective of these arguments, the findings on the relationship between collective efficacy and crime at the street-segment level, to date, are not drawn from direct measures of collective efficacy.

Current Study

Our study advances existing knowledge in two ways. First, we use direct measures (rather than proxy measures) of collective efficacy at a microgeographic unit of analysis, and we are able to control out for a large number of confounding influences. Second, we are able to examine the relationship between collective efficacy and crime at the street-segment level taking into account structural indicators of collective efficacy at the community level.

Street and Survey Samples

The sample used in this paper includes 3,738 residents living on 449 street segments in Baltimore City, MD. Baltimore has a population of over 600,000 people living within 92.1 square miles (US Census Bureau, 2016). The city includes a large minority population (64 per cent African American) and has a poverty rate of 24 per cent—much higher than the national rate of 15.1 per cent (US Census Bureau, 2015). 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). Drug crime in the city was also a serious problem. In 2010, there were more than 52,000 police calls for service (CFS) for drug crime in Baltimore City. The intensity of violent crime and drug problems in the city was a key reason for its selection as a study site. We wanted to be able to identify a large sample of high-rate crime hot spots that could be compared with much lower crime streets in a city.

Street segments serve as the primary unit of analysis in the present study.[1] There are a total of 25,045 street segments (defined as both block faces from intersection to intersection) in Baltimore City. Street segments were selected as the unit of analysis

[1]A detailed description of the sampling approach and methodology for the project is available online: http://cebcp.org/wp-content/cpwg/NIDA-Methodology.

because, as discussed previously, they can be seen as behaviour settings (see Wicker 1987; Weisburd *et al.* 2012, 2014), and they have well-defined and objective boundaries. Furthermore, the use of street segments minimizes the errors likely to develop from miscoding of addresses in official data (see Weisburd and Green 1995; Klinger and Bridges 1997; Weisburd *et al.* 2014).

The sample of street segments was identified using crime calls to the police.[2] While all official measures of crime are imperfect, calls to the police are less likely to be censored by the police than crime incidents that reflect calls that have been 'confirmed' as crimes by police. In turn, given our interest in perceptions of citizens, calls to the police are particularly important. The Baltimore City Police Department, in turn, 'cleans' call information so that each event is only counted once in their database.

We chose to include in the sample only street segments with 20 or more occupied dwelling units to allow for the collection of an adequate number of surveys on each study street segment for the analysis of street-level characteristics.[3] A total of 4,630 street segments met this criterion. We began our sample selection by identifying the top 2.5 per cent of residential streets with drug crime calls and violent crime calls for the entire city in the selection year (2012). This led to three categories of hot spot street segments: violent crime hot spots, drug crime hot spots and combined hot spots that met the criterion for both violent and drug crime.

Hot spot street segments were then sampled from these three respective groups 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 the sample of residential street segments was 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. These site visits were also used to ensure that potential study sites did not have any unusual barriers (e.g. bridges and alley ways) that would significantly affect the behaviour setting of the location. We replaced streets in this process as necessitated to reach our sample goals.[4] The final street segments selected for each of the hot spot categories were all within the top 3 per cent of street segments in the city for that type.

To identify a comparison group of 'non-hot spot' streets, street segments that did not meet the hot spot crime thresholds and that were outside a one-street buffer area from sampled segments were selected randomly using Model Builder. Based on a review of the distribution of crime calls on these 'non-hot spot' streets, we selected out streets with three or fewer crime calls for drug or violent crime and defined them 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.

Descriptive data on crime and disorder calls for the sample of street segments are reported in Table 1. This table demonstrates the high levels of crime in hot spots.

[2]Crime call data for 2012 were obtained from the Baltimore City Police Department and geocoded to the street centreline. 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 per cent.

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

[4]We sought to identify 125 streets for the violent and drug crime hot spots and 50 combined drug and violent crime hot spots. We also sought to include 150 non-hot spot streets in our sample. The final sample numbers depart slightly from these because of one street being dropped from the study during data collection and cases where street segments were reclassified when street boundaries were corrected.

Table 1 *Mean (SD) 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)

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 0.19 drug crime calls. Violent and drug hot spots have, on average, fewer than half as many crime calls as combined hot spots but six or seven times as many calls as cold spots. Finally, cool spots have, on average, more than twice as many calls as cold spots but less than half as many calls as the drug or violent crime hot spots.

Figure 1 shows the location of the different types of crime spots within Baltimore City, MD, that are in the study sample. As is apparent from Figure 1, the five street segment types appear to be spatially heterogeneous, though the crime hot spots are more likely to be located in the central areas of the city.

Microlevel collective efficacy data and street-level control covariates were obtained through in-person, door-to-door surveys and physical observations collected in 2013–14 on the 449 street segments in our study. Interviewers went to sampled street segments in random order (identified within small-area clusters) and interviewed the first adult resident (21 years or older) contacted at the selected dwelling unit who had lived on the street for at least three months. Interviewers returned to the same streets an average of four times and as many as 25 times. The interviewing time frame included mornings, afternoons and early evenings. After adjusting for abandoned housing, our contact rate was 71.2 per cent. The cooperation rate was 60.5 per cent, which is above average for door-to-door surveying (Babbie 2007; Holbrook *et al.* 2008). Surveys took an average of 20 minutes and respondents were given $15 for their participation. The survey was conducted between September of 2013 and May of 2014, with an average of eight surveys completed on each street. During the same period, the field researchers also conducted physical observations of the sampled street segments during separate visits where they documented the physical environment and land use measures of the street, such as building counts, uses and vacancies, as well as aspects of disorder like broken windows, graffiti and litter.

Household survey responses were aggregated to the street-segment level and nested within Community Statistical Areas (CSAs). The CSA serves as the neighbourhood-level unit of analysis for the present research. The Baltimore City Department of Planning and Baltimore Data Collaborative divided the city of Baltimore into 55 CSAs to be more consistent with perceived neighbourhood boundaries. Four guidelines were followed when constructing CSAs: (1) the boundaries had to align with Census Tracts, (2) consist of one to eight 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). They are often used for the purpose of social planning and tracking trends in city conditions and demographics and are frequently used in community

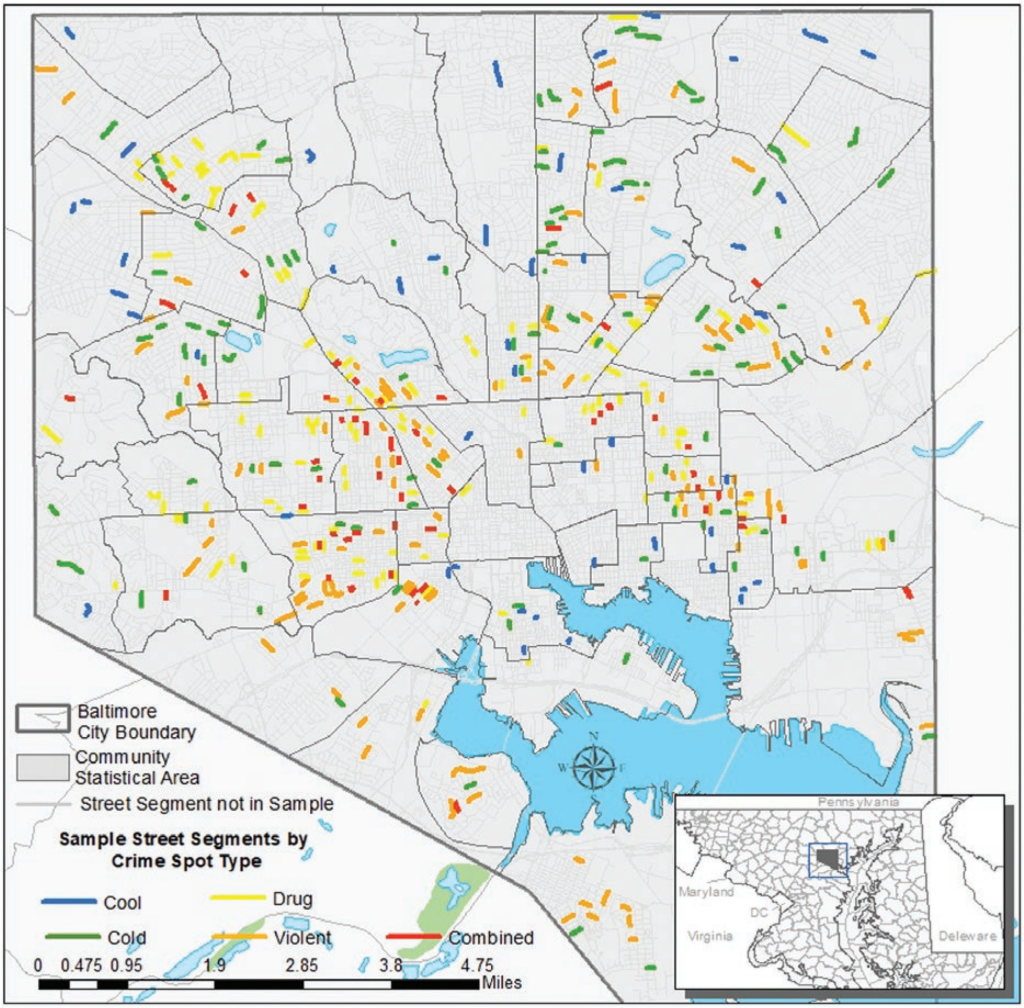

FIG. 1 Study sample street segments by crime type in Baltimore City, MD

research across a number of disciplines (Merse *et al.* 2008; Whitehill *et al.* 2013; Gomez 2016). The CSAs are outlined in the map in Figure 1.

Measures of Collective Efficacy

The items used in the survey to measure collective efficacy followed those in the original development of the concept (see Sampson *et al.* 1997). However, the questions were asked in reference to the *street segment* in which respondents lived rather than the larger neighbourhoods in which they reside. The six items measuring social cohesion and trust asked the respondents about whether neighbours share the same values, can be trusted, get along, help each other, talk to one another and watch out for each other. The items pertaining to willingness to intervene asked about respondents' perceptions of neighbours' likelihood or willingness to intervene in a number of situations, such as kids skipping school, kids spraying graffiti, a fight occurring in front of your home and the closing of a local fire station. The questions were measured on a five-point Likert scale ranging from *strongly disagree to strongly agree* for social cohesion/trust and *very unlikely to very likely* for willingness to intervene.[5] A list of all the items from the survey are included in Table A1. Mean scales for each measure, social cohesion/trust and willingness to intervene, were calculated for each individual, which were then combined and averaged for an overall collective efficacy score.[6] We, then, aggregated (averaged) at the street-segment level to create a street-level measure of collective efficacy ranging from 2.69 to 4.56 with a mean level of overall collective efficacy of 3.65 (standard deviation [SD] = 0.32). High values on the collective efficacy scale correspond to the presence of social cohesion/trust and willingness to intervene on the street.

We could not directly measure collective efficacy at the CSA level by aggregating our street-level samples because in many cases the *N*s are too low in CSAs to gain meaningful estimates. As such, we do not have a direct measure of collective efficacy for CSAs in Baltimore. Instead, we include a group of structural covariates of collective efficacy collected at the CSA level (Sampson and Groves 1989; Sampson *et al.* 1997; Hipp and Wickes 2017). Since CSAs are comprised of census tracts, Baltimore City provides aggregated census data at the CSA level. We included a community-level concentrated disadvantage index composed of percentage of female-headed households, percentage of poverty, percentage of received public assistance and percentage of unemployed (eigenvalue= 3.35, factor loadings > 0.80), a measure of racial diversity and age composition of the CSA.[7] Racial diversity is a measure created and defined by the census, which is the likelihood of selecting two people at random in a neighbourhood and each being a different racial or ethnic group. Finally, we included a measure of the percentage aged 19–24 years old at the CSA level.

Control Variables

Since we are primarily interested in the role of collective efficacy on the street, we controlled for a number of street-level confounders to ensure that the observed relationship between collective efficacy and crime was not due to other characteristics of the street. Given the large number of individual variables in the survey data that we wanted to account for, we conducted a number of principal components factor analyses that reduced the number of covariates in the model while also capturing underlying concepts related to opportunity structures and characteristics of the environment and residents.

To begin, we included a measure of age, gender and socio-economic status. *Age* is a continuous measure of the mean age of residents on the street ranging from 25.1 to 63.6 with a mean of 43.9-years old. *Gender* is the percentage of residents on the street that are female and the mean in our sample of streets was 57.4 per cent female.

[5]Similar to the approach of Sampson *et al.* (1997) and others (Armstrong *et al.* 2015; Sampson and Raudenbush 1999), we recoded 'don't know' responses as a middle category (3) in the five-point Likert scale to represent 'neither agree or disagree' and 'neither likely or unlikely'.

[6]There was a small number of surveys that had missing data for one of the items (less than 1 per cent). We chose to create a mean scale rather than additive, so cases with missing items would not be excluded.

[7]We also considered a measure of residential mobility—percentage of homes that were owner occupied, but it was highly correlated with concentrated disadvantage, so we removed it from the models.

Four street-level measures—percentage of White, mean income level, percentage who are employed full time or part time and percentage with Bachelor's degree or higher, loaded onto a single factor in the factor analysis (eigenvalue = 2.68; factor loadings > 0.72) for the measures of s*ocio-economic status*.

We also included measures of youth presence, physical disorder, urbanization, business activity, public transportation, street population and social services to control for theoretically relevant variables. Family disruption and unsupervised peer groups are key variables in social disorganization theory (Sampson *et al.* 1989); therefore, we included a measure of y*outh presence* comprised of the percentage of single-parent households on the street and a ratio of youth to adults living on the street (eigenvalue = 1.58; factor loadings > 0.89).[8]

Physical disorder included a number of measures from the physical observation data that separated into two distinct measures of physical disorder in the factor analysis, one related to sidewalk and street disorder and the other to structural disorder and dilapidation of the buildings. *Sidewalk physical disorder* was comprised of measures of the amount litter on the street and sidewalk, broken bottles and glass and cigarette and cigar butts (eigenvalue = 2.19; factor loadings > 0.82). *Structural physical disorder* included measures of the number of buildings with broken windows, burned and boarded up buildings and vacant lots (eigenvalue = 1.76; factor loadings > 0.72). *Urbanization* is also another important component of social disorganization theory (Sampson *et al.* 1989) that we controlled for by including a measure comprised of distance from the street segment to the city centre and percentage residential buildings (eigenvalue = 1.13; factor loadings > 0.75).[9]

In regard to measures related to the land use of the street, a measure of *business activity* was included that was comprised of the number of businesses on the street, as well as the number of employees (eigenvalue = 1.80; factor loadings > 0.95). Public transportation and street population are also important aspects of opportunity theories of crime that we included in the analysis (Weisburd *et al.* 2012). To assess the presence of public transportation, we included a measure of the number of *bus stops* within a quarter mile of the street segment. *Street population* was calculated by multiplying the mean number of people living in the households where surveys were completed by the number of occupied households on the street.[10] Finally, the presence of a *social*

[8]Both of these measures were based on questions from the residential survey that asked about number of adults and minors in the household. Our intent was to measure the presence of youth on the street, so we used a measure of single-parent household, 7.2 per cent ($n = 269$) of the sample, rather than the traditional female-headed household, 5.8 per cent ($n = 215$) of the sample. Since there is a great deal of overlap and no substantive changes in results, we opted to use the more inclusive measure of single-parent household.

[9]The city centre was identified using Google Earth and is located at the intersection of N. Calvert Street and E. Fayette Street. Euclidian distance was used to calculate the distance between the centroid of the street segment and the city centre. The number of residential buildings was measured during the physical observations through counts of building for different purposes—residential, commercial and public/social service.

[10]Occupied households were calculated by subtracting vacant dwelling units from the total number of dwelling units on the street segments. Indicators of vacancy were used to identify vacant dwelling units and buildings, such as boarded up doors and windows, eviction notices and realtor lock. One possible bias in our estimates of street population relates to prior findings that single-parent or single-occupant households are less likely to participate in surveys (Tourangeau and Plewes 2013). Nonetheless, in our study, hot spot streets are much more likely to include single-parent households, but they are also streets where our response rates were highest (likely because the compensation provided was more meaningful economically than for people living on better off cold and cool streets). In turn, while high-crime streets have been found to have lower response rates (Tourangeau and Plewes 2013), in our study, these streets have the highest response rates. While we can expect biases related to the response rates, we think that our approach provides a stronger method for identifying street population than using census data that are not collected at the street-segment level. In turn, our finding that street population is strongly predictive of crime is consistent with earlier studies using alternative proxy measures (e.g. see Weisburd *et al.* 2014).

service building on the street was also measured during the physical observations when identifying and counting different building functions on the street.

Analytic Strategy

The analyses for the present research were conducted in two stages. First, analysis of variance (ANOVA) was employed to explore street-level variation in collective efficacy by whether the street segment is classified as a cold, cool, drug, violent or drug/violent (referred to as combined) hot spot. A separate ANOVA was also conducted to examine variation between drug, violent and combined hot spots (excluding residential streets classified as cold and cool spots).

In the second stage of our analysis, a series of multilevel mixed models were conducted to determine the extent to which collective efficacy at the street-segment level is related to microlevel crime levels. We use 2015 crime call data in order to have the crime outcome occur after the data collection. We include the street-level control measures listed above and also conditioned the models based on structural measures at the CSA level that have been used as indicators of collective efficacy.

Results

The ANOVA results for the collective efficacy measure across street types are presented in Table 2. The mean score on the collective efficacy scale was significantly different across the five street segment types (F= 25.95; $p \le 0.001$). Specifically, the mean score on cold streets was 3.95 (SD = 0.25) compared to 3.60 (SD= 0.31) on the drug hot spots, 3.53 (SD = 0.30) on the violent hot spots and 3.52 (SD = 0.32) in the combined hot spots. Cool spots were in the middle with a mean score of 3.77 (0.25). Additionally, when performing the F-test excluding the cold and cool spots, there was no significant difference in collective efficacy across the different types of crime hot spots.

To gain a perspective of the magnitudes of these differences, Table 3 reports the percentage of citizens who respond agree or strongly agree to the social cohesion and trust items or likely and very likely to the willingness to intervene items in the survey by

Table 2 *Analysis of variance for collective efficacy scale by street segment type*

	Type of street segment				
	Cold	Cool	Drug	Violent	Combined
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Collective efficacy	3.95 (0.25)	3.77 (0.25)	3.60 (0.31)	3.53 (0.30)	3.52 (0.32)
F (all groups)	25.95***				
F (excluding cold/cool)	2.27				
n	47	100	121	126	55

***$p \le 0.001$.

Table 3 *Analysis of variance for measures of collective efficacy (percentage of strongly agree or agree) by street segment type*

	Type of street segment				
	Cold	Cool	Drug	Violent	Combined
	%	%	%	%	%
Social cohesion and trust					
People on your block are willing to help their neighbours***	90.9	84.0	79.0	77.5	75.6
Neighbours do not usually talk to each other on your block (reverse coded)*	78.4	76.2	76.8	71.3	73.1
In general, people on your block can be trusted***	84.3	69.6	60.5	51.4	49.1
People on your block usually do not get along with each other (reverse coded)***	90.1	81.4	74.3	71.3	71.9
People on your block do not share the same values (reverse coded)***	65.7	52.9	49.3	44.6	46.6
Neighbours watch out for each other on your block***	90.6	84.2	81.1	76.7	78.3
Willingness to intervene					
If some kids were skipping school and hanging out on your block?***	64.2	62.8	56.4	53.0	55.7
If a group of kids was spraying graffiti on a building?***	92.3	86.5	79.0	76.0	76.1
If a teenager was showing disrespect to an adult?	68.8	71.7	68.3	66.8	66.9
If there was a fight in front of your home?***	88.5	82.9	75.4	73.1	70.8
If a group of kids was climbing on a parked car?***	92.1	89.2	83.2	81.5	77.6
If the local fire station was going to be closed down because of budget cuts?***	76.2	72.8	67.4	65.0	64.4
n	47	100	121	126	55

*$p \leq 0.05$; ***$p \leq 0.001$.

street type. Overall, nearly every item is statistically different across the different street segment types, except for willingness to intervene if a teenager was showing disrespect to an adult, which was similar across the streets ranging from 66.8 to 71.7 per cent. The most notable differences between combined and cold spots for the social cohesion and trust measures were for trust (84.3 vs. 49.1 per cent), getting along with each other (90.1 vs. 71.9 per cent) and sharing the same values with people on your block (67.5 vs. 46.6 per cent). Large differences were also found for willingness to intervene measures (e.g. for a fight in front of their home, 85.5 vs. 70.8 per cent; for a group of kids climbing on a parked car, 92.1 vs. 77.6 per cent)

Multilevel models

Of course, a key concern is whether the observed relationship between collective efficacy and crime at the street segment noted in Table 2 remains salient after we have taken into account covariates at the street-segment level and structural variables strongly related to collective efficacy at the community level (see Table A2 for descriptive statistics for variables in the model).

Table 4 presents the results from a series of multilevel mixed-effects negative binomial regression models relating total crime at the street-segment level as the outcome variable with collective efficacy at the street, other street-level control variables and

Table 4 *Two-level negative binomial model of total calls for service*

	Model 1 (unconditional)		Model 2 (Collective efficacy only)				Model 3 (full model)			
	b	SE	*b*	IRR	SE	*p*-value	*b*	IRR	SE	*p*-value
Fixed effects										
Intercept	4.256***	0.070	6.927***	–	0.413	0.000	4.941***	–	0.413	0.000
Street-level variables										
Collective efficacy	–	–	−0.730***	0.482	0.109	0.000	−0.296**	0.744	0.098	0.003
Age	–	–	–	–	–	–	0.001	1.001	0.005	0.826
Female	–	–	–	–	–	–	0.001	1.001	0.002	0.653
Socio-economic status	–	–	–	–	–	–	−0.225***	0.798	0.041	0.000
Youth presence	–	–	–	–	–	–	−0.046	0.955	0.033	0.156
Sidewalk physical disorder	–	–	–	–	–	–	0.157***	1.170	0.035	0.000
Structural physical disorder	–	–	–	–	–	–	0.049	1.050	0.033	0.143
Urbanization	–	–	–	–	–	–	−0.111**	0.895	0.041	0.006
Business activity	–	–	–	–	–	–	0.113***	1.120	0.036	0.001
Bus stops	–	–	–	–	–	–	−0.006	0.994	0.005	0.237
Street population	–	–	–	–	–	–	0.003***	1.003	0.000	0.000
Social service building	–	–	–	–	–	–	−0.054	0.948	0.073	0.460
Community-level variables										
Concentrated disadvantage	–	–	–	–	–	–	0.075	1.078	0.055	0.172
Racial diversity	–	–	–	–	–	–	0.003	1.003	0.002	0.066
% aged 19–24	–	–	–	–	–	–	−0.013	0.987	0.007	0.053
Random effects										
τ00	0.157		0.101				0.006			
χ^2	32.99***		23.89***				0.77			
Log likelihood	−2,368.635		−2,346.584				−2,248.065			

Incidence rate ratio (IRR) = exp(*b*)
$*p \leq 0.05$; $**p \leq 0.01$; $***p \leq 0.001$.
n = 449 streets (Level 1); n = 53 CSAs (Level 2).

indicators of collective efficacy at the neighbourhood level.[11] To begin, we estimated the unconditional model (Model 1). The likelihood ratio test for the random effects variance component was statistically significant ($\chi^2 = 32.99$; $p \leq 0.001$), indicating that street-level crime varied significantly within communities and supporting the use of multilevel modelling.

We, then, included street-level collective efficacy in Model 2.[12] Following our ANOVA analysis, higher levels of collective efficacy on the street were significantly related to lower crime levels on the street. Finally, in the full model (Model 3), we include the

[11]We also conducted the multilevel models using crime incidents as the measure of crime. Collective efficacy remains significant with a relatively similar effect size.

[12]Following Sampson *et al.* (see Sampson *et al.* 1997; Sampson 2006; 2012), we measure collective efficacy as a single construct. However, we recognize that some scholars have criticized the combination of willingness to intervene and cohesion/trust into a single measure (e.g. see Armstrong *et al.* 2015). The relationship between the two sets of measures are strong in our data ($\alpha = 0.66$).

control variables at the street-segment level, as well as the CSA-level variables. While the importance of collective efficacy declines in this model, it remains an important influence and is statistically significant ($p = 0.003$). A one-unit increase in collective efficacy would be expected to lead to about 25 per cent decline in the crime rate of a street.

Five of the control variables at the street-segment level are statistically significant in the model. Following earlier studies of street segments (e.g. see Weisburd *et al.* 2012), population at the street segment is a key covariate, with higher crime rates on higher population streets. Following social disorganization theory both physical disorder and socio-economic status, as well as urbanization, were found to be strongly significant, with higher levels of urbanization and disorder and lower socio-economic status related to higher levels of crime. Consistent with opportunity theories of crime, more business activity was related to more crime. Structural measures at the community level were not statistically significant.

Discussion and Conclusions

We find that collective efficacy at the street-segment level is strongly related to crime at the street segment, even after taking into account a series of relevant street-level measures, as well as structural variables at the community level. Our results accordingly challenge scholars that argue that the concept of collective efficacy is not relevant to the street-segment level (Sherman *et al.* 1989; Braga and Clarke 2014), as well as those that argue that there is a division of labour between collective efficacy and situational factors (Wilcox *et al.* 2003; 2007; Wikström *et al.* 2010; Braga and Clarke 2014; Bannister *et al.* 2019; Wilcox and Tillyer 2018), with the former operating only at the community level and the latter operating only at the microgeographic level. In this sense, we find that collective efficacy matters at the microgeographic level.

We believe that there is strong theoretical justification for these findings. As we noted earlier, street segments can be seen as microcommunities. In collective efficacy theory, it is the cumulative familiarity of community residents that is the basis for the development of mutual trust, which supports the willingness to intervene and is necessary to the ability of community members to achieve their shared goals. It seems reasonable that familiarity will be greatest on the immediate streets where people live. These are the places where people see each other on a regular basis, and people often interact with their neighbours either to solve specific problems on the street or often to socialize in contacts such as block parties. In this context, crime on a specific street where someone lives would be expected to be related strongly to their self-reports of collective efficacy.

As we discuss below, caution should be exercised in drawing strong conclusions from our finding that structural variables reflecting collective efficacy (rather than collective efficacy in itself) at the neighbourhood level were not important in understanding street-level crime. Nonetheless, we think that the relative importance of street-level collective efficacy in understanding crime at the street level is plausible. One of the most consistent findings of recent decades is that there is a great deal of variability of crime within communities (see earlier). And, more generally, it appears that the 'action' of crime is greater at units such as street segments than neighbourhoods or communities (e.g. see Groff *et al.* 2010; Steenbeek and Weisburd 2016). While social disorganization theorists have focused on large geographic units like 'delinquency areas', the action of crime is often at a much lower geographic level. In turn, the most visceral context for collective efficacy may simply occur in the relationships of people to the microcommunities that surround them. As a Chinese proverb suggests, 'neighbours next store are more important than relatives far away' (Weisburd *et al.* 2012: 3). The strength of collective efficacy as a predictor at the street-segment level, as contrasted with structural covariates at the neighbourhood level, is not surprising in this context.

We also think our data point to the potential of collective efficacy to be harnessed for crime control in crime hot spots. To date, hot spots policing programs have been focused on deterrence or opportunity reduction (Braga *et al.* 2014). Our data suggest that it is time to consider the social context of places in developing hot spots policing and other microgeographic crime prevention programs (see also Weisburd *et al.* 2014; Weisburd *et al.* 2015). While such approaches are just beginning to be developed, there is preliminary evidence that police can work more directly to strengthen microgeographic communities. In Brooklyn Park Minnesota, the Assets Coming Together program sought to use patrol officers to increase collective action and collective efficacy at crime hot spots. Patrol officers identified community members that were willing to work cooperatively with the police and other community members and, then, with them, organized community meetings that identified problems and drew up collaborative efforts for solving those problems. An experimental evaluation of the program showed that citizens in the program sites were more likely to work with police and to have participated in problem-solving efforts with their neighbours than those in the control sites, and there is preliminary evidence of crime prevention impacts (Weisburd *et al.* in press.). Such approaches focus on strengthening microgeographic communities and reinforce both for the police and the public the importance of recognizing and taking into account the people who live in hot spots of crime. It is not simply that such recognition will foster better relationships with the public, our findings suggest it will also help to reduce crime.

Finally, we want to note the specific limitations of our study in drawing broad conclusions about the relationship between collective efficacy and crime. First, we recognize that a longitudinal study of the relationship between collective efficacy and crime would allow for stronger causal conclusions. Indeed, we encourage other researchers with longitudinal data to examine these questions. At the same time, we think our data provide an important proof of concept and suggest the importance of further study of this issue. Our findings also suggest the potential importance of developing similar analyses of related constructs, like perceived police legitimacy, perceived police trustworthiness (procedural justice, distributive justice and effectiveness) and legal cynicism.

Second, we could not identify a direct measure of collective efficacy at the community level. Instead, we used proxy structural indicators that have been found to be strongly related to collective efficacy in communities (i.e. concentrated disadvantage and racial heterogeneity). We think it was sufficient to allow us to test our specific question—does the relationship between collective efficacy and crime remain salient after controlling for community indicators? Indeed, the fact that the relationship persisted after taking into account concentrated disadvantage in the community, arguably one of the most commonly used measures to capture the concept of social disorganization, adds strength to our general argument. At the same time, the lack of a direct measure of collective efficacy at the community level limits our ability to draw strong conclusions regarding the relative impacts of community- versus street-level collective efficacy.

Our paper presents the first examination of levels of collective efficacy and crime using a direct measure of collective efficacy at the microgeographic level. We find that there is a strong relationship between collective efficacy and crime, with crime hot spots evidencing significantly lower levels of collective efficacy than what we termed cool and cold spots. Importantly, the relationship between collective efficacy and crime at the street-segment level remained salient after key covariates and community indicators of collective efficacy were taken into account in a multilevel model. We think these findings are important in that they suggest the relevance of collective efficacy to understanding and controlling crime at microgeographic units.

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Appendix

Table A1 *Measures of collective efficacy*

Social cohesion and trust: For each of the following statements, please tell me if you strongly agree, agree, disagree or strongly disagree.
a. People on your block are willing to help their neighbours
b. Neighbours do NOT talk to each other on your block
c. In general, people on your block can be trusted
d. People on your block usually do NOT get along with each other
e. People on your block do NOT share the same values
f. Neighbours watch out for each other on your block
Willingness to intervene (informal social control): Please tell me if it is very likely, likely, unlikely or very unlikely that the following things would happen on your block.
a. If some kids were skipping school and hanging out on your block, how likely is it that your neighbours would do something about it?
b. If a group of kids was spraying graffiti on a building, how likely is it that your neighbours would do something about it?
c. If a teenager was showing disrespect to an adult, how likely is it that your neighbours would say something?
d. If there was a fight in front of your home, how likely is it that your neighbours would do something about it?
e. If a group of kids was climbing on a parked car, how likely is it that your neighbours would say something to them?
f. If the local fire station was going to be closed down because of budget cuts, how likely is it that your neighbours would do something about it?

In the survey we define block as [STREET NAME] *between STREET A and STREET B*, including both sides of the street.

Table A2 *Descriptive statistics of variables*

	Mean (SD) or %	Range
Street-level data (n = 449)		
Dependent variable		
Total calls for service	81.47 (64.63)	2.00–506.00
Independent variables		
Collective efficacy	3.65 (0.32)	2.69–4.56
Age	43.94 (6.75)	26.13–63.56
Gender (female)	57.37 (18.59)	10.00–100.00
Socio-economic status (factor score)	0.00 (1.00)	–1.41–3.74
Youth presence (factor score)	0.00 (1.00)	–1.31–5.99
Sidewalk physical disorder (factor score)	0.00 (1.00)	–1.27–2.09
Structural physical disorder (factor score)	0.00 (1.00)	–0.69–5.94
Urbanization (factor score)	0.00 (1.00)	–5.95–2.39
Business activity (factor score)	0.00 (1.00)	–0.47–11.87
Bus stops	12.62 (5.58)	0.00–30.00
Street population	143.08 (90.35)	39.00–733.88
Social service building (y/n)	20.27% (0.40)	0–1
Community-level data (n = 53)		
Concentrated disadvantage	0.06 (0.962)	–1.55–2.03
Racial diversity	36.53 (22.58)	7.33–77.77
% aged 19–24	12.06 (5.00)	4.20–33.87

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