Article

Journal of Research in Crime and Delinquency
2018, Vol. 55(3) 425-459

DOI: 10.1177/0022427818758375
journals.sagepub.com/home/jrc
SAGE

The Seasons They Are a Changin': Testing for Seasonal Effects of Potentially Criminogenic Places on Street Robbery

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Abstract

Purpose: To examine a component of crime pattern theory by exploring whether the spatial predictors of crime vary across seasons. *Methods:* The relationships among potentially criminogenic places and illicit markets and seasonal census block robbery counts in Philadelphia, PA, were explored using simultaneously estimated negative binomial regression models. The equality of predictors' effects on street robbery across seasons was subsequently tested using Wald's tests. *Results:* While many facilities and illicit markets were positively associated with street robbery, there were few seasonal differences in their effects. Only the effect of high schools during the fall was greater than during the winter and summer as hypothesized.

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Conclusions: The results suggest areas with facilities and illicit markets that are used consistently across the year experience the highest street robbery levels regardless of the season.

Keywords
crime pattern theory, routine activities theory, facilities, seasonality

Rational crime control policies should be based on sound theoretical explanations of the causes of crime (Mears 2007; Taylor 2015:20-21). Recently, environmental criminology has underpinned many important innovations in crime control policy (Cullen 2011). For example, opportunity reduction via problem-oriented policing in hot spots is regarded as one of the most effective modern policing tactics (Braga, Papachristos, and Hureau 2014). A key axiom of environmental criminology is that crime is concentrated in space *and* time, thus it follows that spatial-temporal concentrations have been assumed to be important for understanding and addressing crime problems (e.g., see Clarke and Eck 2005, Steps 25-26). A large body of research has consistently shown that crime is concentrated in space (Weisburd 2015), but much less is known about spatial *and* temporal crime patterns. Most environmental criminology research to date has been *atemporal* (Haberman, Sorg, and Ratcliffe 2017). This research tends to demonstrate a disproportionate level of crime is concentrated in few places or explain those concentrations by regressing crime levels from a single year on characteristics of the built and social environment. By design, these studies assume the observed effects are temporally invariant despite environmental criminology's axiom that space *and* time are important for understanding crime patterns.

The few studies that have examined spatial-temporal crime patterns to date have focused on within-day spatial-temporal patterns and generally found that crime concentrates in busy places regardless of time of day (e.g., see Bernasco, Ruiter, and Block 2017; Haberman and Ratcliffe 2015). A large body of research dating back to the 1800s, however, has argued that crime is seasonal, and environmental criminology theories have become the widely accepted explanation of seasonal crime patterns. Nonetheless, we demonstrate below that existing research has not adequately tested whether the predictors of spatial crime patterns vary across seasons as predicted by environmental criminology theories. Given the importance of environmental criminology for current and future (unknown) crime control policy, science that tests environmental criminology's core yet untested hypotheses is imperative for further developing the theory as well as its implications for crime control policy.

Therefore, this study used data on potentially criminogenic facilities and illicit markets to test whether the effects of these predictors on geographic street robbery levels are different across seasons in Philadelphia (net of sociodemographics). Specifically, we outline hypotheses of how different potentially criminogenic facilities might link to geographic street robbery levels across different seasons according to environmental criminology. We then use simultaneously estimated negative binomial regression models and equality of coefficient tests to *directly* examine whether some predictors have greater effects during some seasons than others. Except for high schools, the effects of potentially criminogenic facilities and illicit markets on street robbery were not seasonal. Thus, we conclude by discussing the importance of these findings for understanding spatial-temporal crime patterns using environmental criminology theories.

Literature Review

Theories of Seasonal Crime Patterns

The existing studies of seasonal crime patterns generally note that the literature on the topic dates to at least the 1800s (usually by citing Quetelet 1842). Researchers have long focused on explaining how and why some crimes peak at some times of the year (Baumer and Wright 1996; Cohn 1990). Early research mostly posited that humans' psychological response to higher temperatures could explain seasonal violence patterns (Rotton and Cohn 1999). Early laboratory studies found that humans responded more aggressively as ambient temperature increased (Baron and Bell 1976). Researchers later debated whether the relationship between temperature and crime levels is linear (general affect model) versus curvilinear (negative affect escape model; Anderson and DeNeve 1992; Bell 1992; Cohn and Rotton 1997; Rotton and Cohn 1999), but correlations have been found between ambient temperature and aggregate violence levels (e.g., see Field 1992; Lab and Hirschel 1988; Rotton and Frey 1985).

Nonetheless, researchers eventually started to question the utility of hypotheses stressing the importance of humans' response to temperatures for explaining patterns of other crime types (e.g., property crime; Hipp et al. 2004). Many researchers started to argue that routine activities theory (RAT) could better explain the relationship between temperature and all crime types (Andresen and Malleson 2013; Cohn and Rotton 1997; Cohen and Felson 1979; Rotton and Cohn 1999). It was theorized that changes in weather/seasons could impact a person's routine activities and thus change the availability of crime opportunities. Scholars then started to explain the correlation among ambient temperature or other weather measures (e.g., precipitation and wind speed) and different crime types using a RAT framework (Cohn and Rotton 1997; Linning, Andresen, and Brantingham 2016; Rotton and Cohn 1999). In fact, some studies suggested that RAT provided the "best" explanation of the relationship between weather and within-year variation in crime levels (Cohn and Rotton 2000; Hipp et al. 2004; McDowall, Loftin, and Pate 2012).[1]

Environmental Criminology

Outside of seasonal (or temporal) patterns, a large body of research has found that certain types of places link to higher crime levels. A representative but nonexhaustive list of places linked to higher crime levels includes: ATMs and banks (Haberman and Ratcliffe 2015), bars (Groff 2011; Roncek and Bell 1981; Roncek and Maier 1991), check cashing facilities/payday lenders (Kubrin et al. 2011), drug markets (Johnson 2016), fast-food restaurants (Bernasco and Block 2011; P. L. Brantingham and Brantingham 1981), gang territories (Taniguchi, Ratcliffe, and Taylor 2011), parks (Groff and McCord 2011; McCord and Houser 2015), public housing (Haberman, Groff, and Taylor 2013), public transportation (Block and Block 2000; Block and Davis 1996), and schools (Roman 2005) to name a few.

The research linking (potentially criminogenic) facilities and illicit markets to geographic crime levels stem from environmental criminology's RAT and crime pattern theory (CPT). According to RAT, crime events are the result of motivated offenders converging with suitable targets lacking adequate guardianship in space and time (Cohen and Felson 1979). CPT then spatialized RAT by demonstrating how the urban environment, such as facilities and illicit markets, structure and concentrate the convergence of RAT's three basic elements of crime (P. L. Brantingham and Brantingham 1981; P. J. Brantingham and Brantingham 1993). In short, CPT predicts crime will concentrate in areas where offenders find suitable targets lacking capable guardianship in accordance with humans' routine activity patterns (P. L. Brantingham and Brantingham 1999).

Human routine activity patterns, however, have rhythms across different temporal scales (Hawley 1950). People do different things at different places during different times of the day, days of the week, and seasons of the year. People are generally constrained by their monetary need to participate in the formal economy and biological need to sleep (Hägerstrand 1970). This generates aggregate behavior patterns within and between days with people having greater flexibility for discretionary activities during nights and weekends (see Bernasco et al. 2017; Haberman and Ratcliffe 2015). Further, human routine activity patterns will change throughout the year. People will spend more time engaging in outdoor recreational activities during warmer seasons. Winter and summer school break periods will drastically impact juveniles' (and often their parents') routine activity patterns by giving them increased free time. In the United States, the Thanksgiving through New Year's Day holiday seasons will increase peoples' travel away from home, regardless of the weather. Fall, spring, and summer bring different festivals, sports, and public events that change how people use the urban landscape. Many families will vacation during the summer months because children will not be in school, and pleasant weather conditions make travel more enjoyable.

These temporal rhythms have important implications for spatial-temporal crime patterns (Felson and Eckert 2016). In short, spatial-temporal distributions of crime opportunities are expected to change over space *and* time in accordance with where motivated offenders will find suitable targets lacking capable guardianship (Ratcliffe 2010). In recent years, environmental criminologists have made more concerted efforts to bolster theoretical positions with empirical support (see Farrell et al. 2011; Tseloni et al. 2017; Welsh, Zimmerman, and Zane 2017); however, the research that does exist on spatial-temporal crime patterns has been primarily focused on within-day spatial-temporal crime patterns (Bernasco et al. 2017; Haberman and Ratcliffe 2015). The validity of environmental criminology theories and their potential to inform crime reduction programs (see Cullen 2011) specifically designed at different temporal scales (Andresen and Malleson 2013; Linning et al. 2016) will be expanded by testing hypotheses of spatial-temporal crime patterns at different temporal scales (Haberman et al. 2017).

Environmental Criminology and Seasonal Crime Patterns Research

Past research has found potentially criminogenic facilities and illicit markets generally link to higher crime levels (e.g., see Bernasco and Block 2011); therefore, we hypothesize facilities and illicit markets will generally link to higher crime. If human activity patterns vary over time, particularly across seasons, however, two hypotheses regarding the seasonal impacts of potentially criminogenic facilities can be posed.[2] First, facilities with usage patterns that vary across seasons due to their definitional purpose should have greater effects on crime during high-use seasons when they are facilitating the convergence of motivated offenders and suitable targets lacking capable guardianship. Education institutions should link with crime when they are in session. High schools are typically in session between September and early June yet closed mid-December through mid-January for winter break (e.g., School District of Philadelphia 2012), so they should have strongest link to street robbery during the fall and spring. Higher education institutions follow a similar usage pattern, so their effects should be similar to high schools. Facilities hosting outdoor recreation, such as neighborhood parks, are hypothesized to link to higher street robbery levels during the fall, spring, and summer when the parks attract large numbers of users for recreational activities. Finally, facilities that encourage tourism are hypothesized to link to higher crime most strongly during the summer when the weather is pleasant, and families can travel with children who are out of school.

Second, many facilities are hypothesized to simply link to crime year-round because they are used consistently. For example, patrons need to complete economic/commercial transactions all year, so facilities (e.g., ATMs and banks, alcohol stores, corner stores, check cashing stores, fast-food restaurants, and pawn shops) hosting that activity experience consistent use. Likewise, residential facilities (e.g., public housing communities) are inhabited and used year-round. Finally, residents commuting to work or traveling for personal/recreational reasons use transit facilities (e.g., subway stations) all year.[3]

Despite the potential for the effects of facilities and illicit markets to vary across seasons and a large body of research on seasonal crime patterns, no studies to date have adequately tested the general hypotheses presented above. Past studies of seasonal crime patterns generally suffer from four limitations that preclude drawing strong conclusions about how spatial crime patterns change across seasons in relation to important predictors from environmental criminology theories. We review the studies suffering from these four limitations below.

First, most research on seasonal crime patterns has been *at the macro level*. Some studies have simply tested for seasonal spikes over the course of a year (Falk 1952; Landau and Fridman 1993; Sisti et al. 2012; Yan 2004). Other studies have correlated citywide crime levels with weather or temporal predictors (Cohn and Rotton 1997, 2000; Field 1992; Harries and

Stadler 1983; Heller and Markland 1970; Hipp et al. 2004; Lab and Hirschel 1988; Mares 2013; McDowall et al. 2012; Peng et al. 2011; Rotton and Frey 1985; Tompson and Bowers 2015).[4] Testing environmental criminology theories, however, requires a simultaneous examination of microspatial and temporal crime patterns.

Second, a few studies have shown that crime simultaneously varies across space and seasons but did not attempt to explain "why." Ceccato (2005) found differences in spatial patterns of homicide across seasons in Sao Paulo. Brunsdon and colleagues (2009) found the spatial patterning of disorder and disturbances changed with variations in weather. Andresen and Malleson (2013) found that the geographic locations of many crime types varied across the seasons in Vancouver. While all three studies made important contributions by illustrating spatial crime patterns change across seasons, the authors' explanations for the observed patterns were not directly tested but (reasonably) inferred.

A third line of research has explained neighborhood crime levels with interactions between temperature and neighborhood features. Harries, Stadler, and Zdorkowski (1984) found that temperature had a greater effect on daily assault counts in lower socioeconomic status Dallas, TX, neighborhoods, suggesting residents in disadvantaged neighborhoods become more agitated because they cannot escape the heat through air conditioning. Breetzke and Cohn (2012) also found economically disadvantaged neighborhoods had higher assault rates during summer months and suggested both temperature aggression and RAT could explain the results. While both studies illustrated there may be theoretical reasons that explain why different places have different crime levels across seasons, the studies did little to explain that spatial-temporal variation beyond neighborhood social composition.

Fourth, Sorg and Taylor (2011) provided a spatialized study of crime seasonality aligned with environmental criminology theories and research, but the scope of their study was limited. Specifically, their study found that the impact of average monthly temperature on monthly robbery levels varied across Philadelphia, PA, census tracts. The presence of a subway station intensified the relationship between temperature and street robbery (i.e., a cross-level interaction), which was theorized to be due to "seasonal changes in foot traffic patterns in such communities" (Sorg and Taylor 2011: 465). The authors also noted, based on their knowledge of Philadelphia, that positive values of temperature's varying slope were found in areas where people would be engaged in seasonal outdoor activities (Sorg and Taylor 2011). While this study provided tentative evidence that the effect of at least one facility was seasonally dependent, studies that examine and control for a wider range of predictors would provide a more robust test of the hypotheses stated above.

Therefore, the current study sought to expand the existing literature testing CPT by examining the effect of different potentially criminogenic facilities on seasonal street robbery levels across space. Street robbery was selected for a number of reasons. First, street robbery by definition occurs outdoors and is dependent on at least two humans (a victim and an offender) moving through space. Further, past research suggests street robbery links to busy areas with facilities or illicit markets (Bernasco and Block 2011). Further, street robbery can often be an impulsive crime, driven by opportunity rather than extensive planning (Bernasco et al. 2017). As a result, it is likely to be a crime type more influenced by the variation in human movement patterns across seasons. Finally, because of the need for data accuracy at the spatial and temporal level, street robberies tend to have accurately recorded times, dates, and addresses because victims are present during the events by definition (Haberman et al. 2017).

Data and Method

Study Site and Unit of Analysis

We examined seasonal street robbery counts across census blocks with at least 20 residents in Philadelphia, PA, $n = 13{,}164$. Philadelphia's 1.5 million residents are about equally Black and White (about 45 percent, respectively). Approximately 12 percent of Philadelphians identify as Hispanic/Latino (U.S. Census Bureau 2010a). Philadelphia's median income of $34,207 is about $15,000 less than the national median income (U.S. Census Bureau 2011). About the size of three American football fields (mean study census block area = 0.006 square miles; American football field = 0.002 square miles, see Goodell 2012), census blocks are the smallest spatial units in which social demographic data are freely and publicly available on a regular basis from the U.S. Census Bureau (2010b).

Dependent Variable

The Philadelphia Police Department (PPD) provided crime incident data (2009-2011). PPD geocodes its crime incident data with a roughly 98 percent hit rate, which is above Ratcliffe's (2004) recommended 85 percent hit rate.[5] Street robbery events were identified using Uniform Crime Rreport (UCR) classification codes. Street robbery is the theft of another's property through the use or threat of force by at least one person in a public location (mostly on the street; Monk, Heinonen, and Eck 2010). The dependent variable was operationalized as total street robberies in each census block for each of the four seasons across the three years of data (Bernasco and Block 2011; Haberman and Ratcliffe 2015). Fall spanned from September through November. Winter spanned from December through February. Spring spanned from March through May. Summer spanned from June through August. These periods follow previous research on seasonal crime patterns and leading climate scientists (Andresen and Malleson 2013; Linning 2015; Trenberth 1983). They also capture societal shifts in routine activities across the year. It is important to point out that while weather patterns have considerable impact on seasonal routine activities, these periods were operationalized to capture aggregate seasonal changes in routine activity patterns rather than the immediate effect of weather (as described above). Table 1 displays descriptive statistics for all outcome variables. Figure 1 displays changes in the relative levels of street robbery by season in Philadelphia for each year of the study period as well as the three-year sum outcome. Sensitivity analyses estimating the results for each year of the study period are presented in the Online Supplemental Material and discussed below. Overall, Philadelphia street robbery levels were highest in the fall, dropped to their lowest levels in the winter, and then generally increased in the spring through the summer for each year of the study period as well as for all three years combined.

Independent Variables

Table 1 displays descriptive statistics for all independent variables. Past studies of spatial street robbery patterns (and data access) guided our selection of predictors (Bernasco and Block 2011; Bernasco et al. 2017; Haberman and Ratcliffe 2015). We sought to obtain all measures from past studies as well as any new facilities that represent important nodes in the urban backcloth from readily available sources. Facility data were provided by the PPD or procured from another source.[6] Data were obtained for 14 potentially criminogenic facilities: (1) ATMs and banks (count), (2) alcohol stores (count), (3) bars (count), (4) check cashing stores (count), (5) corner stores (count), (6) drug treatment centers (count), (7) fast-food restaurants (count), (8) high schools (dummy), (9) higher education institutions (dummy), (10) neighborhood parks (dummy), (11) pawn shops (count), (12) public housing communities (dummy), (13) subway stops (dummy), and (14) tourist sites (count).[7] The locations and classifications of all potentially criminogenic facilities were confirmed via Internet searches.[8]

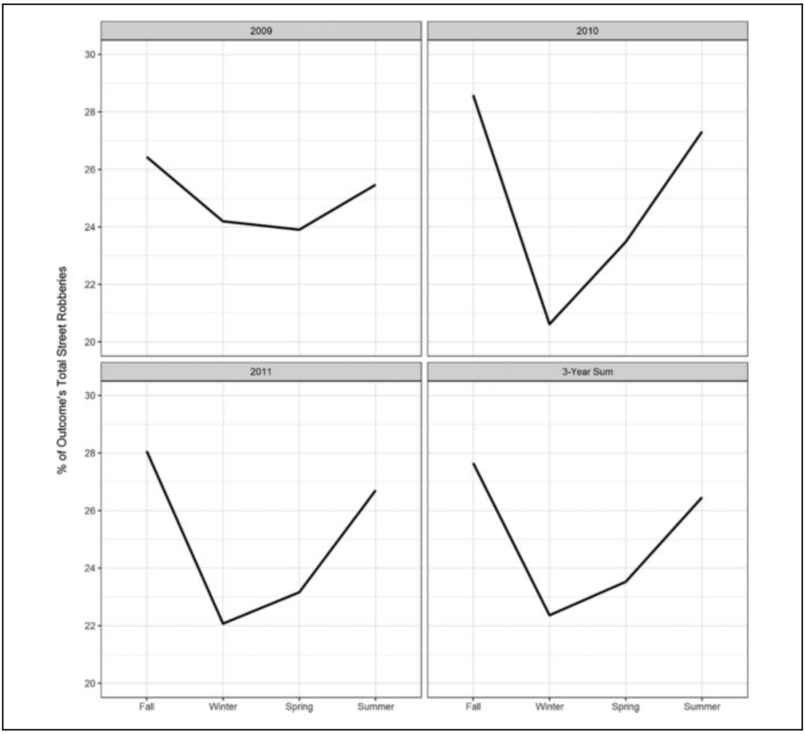

Figure 1. Percentage of outcome's street robberies occurring in each season across the study period. Results presented in the main body of the manuscript use three-year sum outcomes based on 14,588 street robberies. Results for yearly outcomes presented in Online Supplemental Material ($n_{2009} = 5,175$; $n_{2010} = 4,642$; and $n_{2011} = 4,771$ street robberies).

Nearest neighbor hierarchical clustering (Nnh) was used to construct measures of (1) narcotics, (2) prostitution, and (3) gambling markets (see Johnson 2016; Johnson and Ratcliffe 2013; Johnson, Taylor, and Ratcliffe 2013). Nnh is a hot spot identification technique that identifies dense clusters of crime incidents that are close in space (Levine 2015). Using Nnh to identify illicit markets ensures the locations with only the most concentrated patterns of illicit incidents are identified as markets. CrimeStat IV's Nnh algorithm was run separately on PPD's 2009-2011 narcotics distribution ($N = 13,801$), prostitution solicitation ($N = 2,154$), and gambling law violation ($N = 216$) incidents. The threshold distances were set to the random nearest neighbor distance at $p < .05$, the minimum incidents per clusters was set to five, and 999 simulations were used to confirm statistical significance of the output clusters (see Haberman 2017; Levine 2015). The first-order convex hulls for each market type were intersected with the census blocks. Census blocks that intersected with a given illicit market type were coded 1 on that illicit market's predictor and all other census blocks were coded 0.

Based on the communities and crime literature, census block concentrated disadvantage, residential mobility, and racial heterogeneity were included as control variables. The sociodemographic predictors were derived from the 2011 American Community Survey 5-Year Estimates (U.S. Census Bureau 2011). Concentrated disadvantage was the average of three *z*-scored items: (1) percentage of residents 25 years of age or older without a high school degree, (2) median income (multiplied by negative one), and (3) percentage of families in poverty ($\alpha = .90$).[9] Residential mobility was the average of two *z*-scored items: (1) percentage of renter-occupied housing units and (2) percentage of residents who moved in the last year ($\alpha = 44$).[10] The items used to derive the indices were guided by the literature, and a principal components analysis (using varimax rotation) confirmed the items loaded uniquely on just the two indices used. Racial heterogeneity was measured as 1 minus the sum of the squared proportions of five racial groups making up each census block (White, Black, Hispanic/Latino, Asian, and all other races), where values close to zero indicate racial homogeneity and values close to the theoretical maximum ($1 - 1/5$) indicate racial heterogeneity (Chainey and Ratcliffe 2005; Gibbs and Martin 1962). Census block residential population counts were also included as a predictor. These population counts do not capture ambient populations (Andresen 2006, 2010, 2011; Andresen and Jenion 2010) but rather control for baseline population. Based on the study's theoretical frame, the potentially criminogenic places predictors then capture large-scale changes in population due to routine activity patterns (Bernasco and Block 2011; Haberman and Ratcliffe 2015).

Analytic Plan

Simultaneously estimated negative binomial regression models and equality of coefficient Wald's tests were used to test the study's hypotheses (Weesie 1999). Negative binomial regression models are appropriate for modeling overdispersed count outcomes (Hilbe 2007; Osgood 2000). The outcome was confirmed to be overdispersed by (1) comparing the observed street robbery outcomes' distributions to simulated negative binomial distributions (with the same number of cases and means as the outcomes) and (2) examining likelihood ratio tests comparing Poisson and negative binomial models (Long and Freese 2006).

Seasonal street robbery outcomes derived from the same units are dependent observations, and thus the parameter estimates derived from any regression models of the seasonal street robbery outcomes also will be dependent. Simultaneously estimated models account for the lack of independence across the models by estimating the parameters using a single (co)variance matrix (see Weesie 1999: 36). This approach draws on White's (1982) work on "robust standard errors" to ensure the parameter estimates are efficient (i.e., correct standard errors; Weesie 1999: 36). Wald's tests were then used to compare the magnitudes of the coefficients for the potentially criminogenic predictors across seasons (Weesie 1999: 37). All of the predictors described above were entered into the negative binomial model for each season, given the hypothesis that busy facilities link to street robbery (see Bernasco and Block 2011). The large number of predictors increased the likelihood of making a type I error, so Wald's tests were only computed for predictors that were statistically significantly linked to street robbery during at least one season. Further, omnibus tests were initially used to compare the magnitudes of each effect across all models (seasons). If a statistically significant difference was observed in the omnibus tests, then specific tests were performed for a pair of models (i.e., seasons). All analyses were conducted using Stata 13's *suest* and *test* commands (StataCorp 2013).

Two methods were used to account for the data's spatial structure, while ensuring the results were not sensitive to the method used. First, we modeled both the spatially immediate and lagged effects of the potentially criminogenic facilities' predictors. This approach is both theoretically and technically appropriate (see Bernasco and Elfers 2010). CPT predicts that potentially criminogenic facilities may have "spillover effects" on nearby crime levels (Bernasco and Block 2011; Groff 2011; Groff and Lockwood 2014; Haberman et al. 2013; Haberman and Ratcliffe 2015; Ratcliffe 2012). One recent study even found alcohol outlets' effect on crime in nearby areas was larger than their effect on the immediate area (Wheeler 2016). It is also theoretically plausible that some potentially criminogenic facilities affect crime only in nearby areas (and not the immediate area). For example, street robbers could target students near but off university campuses in order to avoid campus security and police. Of course, these are all open empirical questions that require examination. From a technical standpoint, researchers have reported that including spatially lagged (SL) predictors in their models reduced residual spatial autocorrelation (Bernasco and Block 2011; Haberman and Ratcliffe 2015). Spatially autocorrelated residuals suggest the statistical assumption of independent observations is violated. Therefore, SL versions of all potentially criminogenic facility predictors were created using an author written R script and a first-order queen contiguity matrix. Predictors operationalized as counts were simply the sum of neighboring units. Predictors operationalized as dummy variables were simply the presence (1) or absence (0) of the facility in any neighboring unit.

An alternative approach for modeling spatial data is to include a SL version of the outcome measure as an additional predictor (Chainey and Ratcliffe 2005: 135-36). This approach captures the unmeasured spatial effects that are associated with the "diffusion" of crime across neighboring units (Bernasco and Elfers 2010). Omitting SL predictors reduces the potential for Type I errors when comparing coefficients because fewer significance tests are required (Bernasco et al. 2017: 258). Some readers may also question the theoretical contributions of SL predictors. Therefore, we also estimated models with only the facilities' spatially immediate effects on street robbery while including SL versions of the outcomes as a predictor. The SL outcomes were created in GeoDa (version 1.10.0.8.) with a first-order queen contiguity spatial weights matrix. Because we are theoretically interested in the effects of the SL predictors, we present the SL outcome model results in the Online Supplemental Material.[11]

Another sensitivity test considered the results' robustness for different operationalizations of the seasonal street robbery outcomes. Crime and place researchers have rejected the use of models for rare counts (e.g., zero-inflated models) on theoretical grounds (see Groff and Lockwood 2014: footnote 10). An alternative modeling strategy, therefore, is to pool multiple years of data to model rare crime outcomes (e.g., see Bernasco and Block 2011; Haberman and Ratcliffe 2015; Thompson and Gartner 2014). Pooled dependent variables effectively reduce the sparseness and increase the variance of rare crime count outcomes. Since relatively high-crime locations tend to remain high-crime locations relative to all other locations in a city (Braga, Papachristos, and Hureau 2010; Braga et al. 2011; Weisburd et al. 2004; Weisburd, Groff, and Yang 2012; Wheeler, Worden, and McLean 2016), pooled-dependent variables should not change the relative differences (rankings) in crime across units. This is demonstrated empirically for our data in the Online Supplemental Material. The modifiable temporal unit problem (MTUP), however, suggests that statistical results could be sensitive to how temporal units are operationalized and is an important limitation of using pooled outcomes. Therefore, we also

Table 1. Descriptive Statistics for All Model Variables.

Variable	Min.	Max.	Mean	*SD*
Street robbery counts				
Fall	0.00	12.00	.31	0.68
Winter	0.00	10.00	.25	0.61
Spring	0.00	11.00	.26	0.62
Summer	0.00	13.00	.29	0.67
Spatially immediate predictors				
ATMs and banks	0.00	9.00	.06	0.32
Alcohol stores	0.00	2.00	.01	0.09
Bars	0.00	6.00	.04	0.23
Check cashing stores	0.00	3.00	.01	0.11
Corner stores	0.00	3.00	.08	0.30
Drug treatment centers	0.00	4.00	.01	0.09
Fast-food restaurants	0.00	11.00	.13	0.49
High schools	0.00	1.00	.01	0.08
Higher education institutions	0.00	1.00	.03	0.16
Neighborhood parks	0.00	1.00	.10	0.30
Pawn shops	0.00	2.00	.00	0.04
Public housing	0.00	1.00	.02	0.14
Subway stops	0.00	1.00	.01	0.07
Tourist sites	0.00	5.00	.01	0.09
Narcotics markets	0.00	1.00	.13	0.34
Prostitution markets	0.00	1.00	.02	0.15
Gambling markets	0.00	1.00	.03	0.16
Spatially lagged predictors				
SL ATMs and banks	0.00	27.00	.49	1.15
SL alcohol stores	0.00	3.00	.06	0.27
SL bars	0.00	14.00	.26	0.76
SL check cashing stores	0.00	4.00	.08	0.30
SL corner stores	0.00	7.00	.54	0.86
SL drug treatment centers	0.00	4.00	.04	0.23
SL fast-food restaurants	0.00	40.00	.96	1.71
SL high schools	0.00	1.00	.07	0.25
SL higher education institutions	0.00	1.00	.04	0.19
SL neighborhood parks	0.00	1.00	.21	0.41
SL pawn shops	0.00	2.00	.01	0.12
SL public housing	0.00	1.00	.03	0.16
SL subway stops	0.00	1.00	.05	0.22
SL tourist sites	0.00	11.00	.05	0.35
SL narcotics markets	0.00	1.00	.17	0.38
SL prostitution markets	0.00	1.00	.04	0.20
SL gambling markets	0.00	1.00	.03	0.16

(continued)

Table 1. (continued)

Variable	Min.	Max.	Mean	*SD*
Control variables				
Residential population (per 1,000)	0.02	4.54	.12	0.10
SL residential population (per 1,000)	0.00	5.10	.73	0.39
Concentrated disadvantage	−2.48	2.41	.09	0.87
Residential mobility	−1.13	3.66	.12	0.67
Racial heterogeneity	0.00	0.79	.33	0.22

Note: Descriptive statistics computed only for census blocks with at least 20 residents (n = 13,164). SL = spatially lagged; Min. = minimum; Max. = maximum; SD = standard deviation.

examined the results' sensitivity to the MTUP by reestimating the models after disaggregating the seasonal street robbery outcomes for each year (3 years by 4 seasons = 12 models).[12] These sensitivity analyses are shown in the Online Supplemental Material.

Results

Global Moran's I analyses (first-order queen continuity; 999 simulations) suggested that residual spatial autocorrelation was handled appropriately in all models (Anselin 1995).[13] Variance inflation factors (<4) ruled out collinearity (MacDonald and Lattimore 2010). Table 2 shows the parameter estimates from the simultaneously estimated negative binomial regression models estimating the effects of the spatially immediate and lagged predictors on the three-year sum seasonal outcomes. Incident rate ratios (IRRs) are also displayed to simplify interpretation of the effects. IRRs are obtained by exponentiating a model's coefficients. An IRR is converted into a percentage change in the outcome per one-unit increase in a predictor by multiplying the difference between the IRRs and 1 by 100 (Cameron and Trivedi 2013). When interpreting the coefficients, we may talk about percentage changes in "street robbery" more generally to improve readability. Technically, we are implying percentage changes in expected census block street robbery counts per one-unit increase in a predictor. Table 3 shows the corresponding equality of coefficient tests. The Online Technical Appendix displays the results of all sensitivity analyses.

The present findings are consistent with past research and suggest potentially criminogenic facilities and illicit markets are positively associated with street robbery (Bernasco and Block 2011; Bernasco et al. 2017; Haberman and Ratcliffe 2015). A total of 11 potentially criminogenic facilities

Table 2. Simultaneously Estimated Negative Binomial Regression Results.

	Fall			Winter			Spring			Summer		
Variables	Coef.	*SE*	IRR	Coef.	*SE*	IRR	Coef.	*SE*	IRR	Coef.	*SE*	IRR
ATMs and banks	.164**	(.059)	1.178	.263***	(.058)	1.300	.182**	(.060)	1.199	.258***	(.059)	1.295
Alcohol stores	−.166	(.133)	0.847	−.075	(.162)	0.928	.014	(.130)	1.014	−.060	(.154)	0.942
Bars	.151*	(.075)	1.163	.058	(.086)	1.060	.090	(.085)	1.094	.079	(.080)	1.083
Check cashing stores	.284**	(.103)	1.328	−.026	(.140)	0.974	.336***	(.099)	1.399	.162	(.111)	1.176
Corner stores	.210***	(.052)	1.234	.265***	(.054)	1.304	.184***	(.051)	1.202	.135*	(.054)	1.145
Drug treatment	.335*	(.142)	1.398	.124	(.129)	1.132	.314*	(.133)	1.369	.282*	(.141)	1.325
Fast-food restaurants	.089**	(.033)	1.093	.096*	(.040)	1.101	.125***	(.033)	1.134	.122***	(.034)	1.129
High schools	.839***	(.157)	2.315	.321	(.180)	1.378	.343	(.194)	1.410	.413*	(.166)	1.511
Higher education	−.073	(.113)	0.930	−.544***	(.150)	0.580	−.207	(.125)	0.813	−.298*	(.128)	0.742
Parks	.206***	(.057)	1.229	.150*	(.066)	1.161	.244***	(.060)	1.276	.273***	(.060)	1.313
Pawn shops	.412	(.413)	1.511	.798**	(.257)	2.222	.314	(.275)	1.369	.661**	(.254)	1.936
Public housing	.183	(.115)	1.200	.319**	(.123)	1.375	.426***	(.120)	1.531	.136	(.137)	1.145
Subway stations	.777***	(.184)	2.174	.586*	(.241)	1.797	.753***	(.194)	2.124	.814***	(.189)	2.256
Tourist sites	−.111	(.200)	0.895	−.107	(.216)	0.899	−.426*	(.212)	0.653	.056	(.244)	1.058
Narcotics markets	.331***	(.060)	1.393	.390***	(.066)	1.477	.302***	(.064)	1.353	.212***	(.061)	1.236
Prostitution markets	.457***	(.089)	1.580	.366***	(.098)	1.441	.503***	(.094)	1.654	.528***	(.099)	1.695
Gambling markets	.005	(.106)	1.005	−.164	(.129)	0.849	−.126	(.126)	0.882	−.061	(.120)	0.941
SL ATMs and banks	.0001	(.020)	1.000	.010	(.019)	1.010	.010	(.018)	1.010	−.029	(.017)	0.971
SL alcohol stores	−.094	(.064)	0.910	−.144	(.074)	0.866	−.171*	(.068)	0.842	.059	(.059)	1.061
SL bars	−.006	(.027)	0.994	.006	(.029)	1.006	.016	(.027)	1.016	−.002	(.027)	0.998
SL check cashing stores	.154***	(.048)	1.166	.125*	(.054)	1.134	.214***	(.048)	1.239	.193***	(.051)	1.213
SL corner stores	.061**	(.021)	1.063	.060**	(.023)	1.062	.062**	(.022)	1.064	.067***	(.021)	1.070
SL drug treatment	−.027	(.065)	0.973	.142*	(.070)	1.153	.134	(.070)	1.143	.047	(.066)	1.048
SL fast-food restaurants	.049***	(.010)	1.051	.051***	(.012)	1.052	.056***	(.012)	1.058	.051***	(.012)	1.052

(continued)

Table 2. (continued)

	Fall			Winter			Spring			Summer		
Variables	Coef.	*SE*	IRR	Coef.	*SE*	IRR	Coef.	*SE*	IRR	Coef.	*SE*	IRR
SL high schools	.210***	(.064)	1.233	.134	(.082)	1.143	.210**	(.071)	1.234	.091	(.071)	1.095
SL higher education	.342***	(.090)	1.408	.020	(.115)	1.020	.250*	(.110)	1.284	.210*	(.090)	1.234
SL parks	.006	(.045)	1.006	.036	(.050)	1.037	−.008	(.048)	0.992	.036	(.046)	1.037
SL pawn shops	.139	(.100)	1.149	.098	(.107)	1.103	.063	(.111)	1.065	.043	(.110)	1.044
SL public housing	.156	(.095)	1.169	.203	(.107)	1.225	.207*	(.104)	1.230	.245*	(.102)	1.278
SL subway stations	.333***	(.073)	1.395	.460***	(.089)	1.584	.360***	(.083)	1.433	.308***	(.081)	1.361
SL tourist sites	.021	(.061)	1.021	.037	(.062)	1.038	.008	(.063)	1.008	.037	(.062)	1.038
SL narcotics markets	.141**	(.054)	1.151	.209***	(.061)	1.232	.163**	(.057)	1.177	.057	(.055)	1.058
SL prostitution markets	.173*	(.078)	1.189	.179	(.097)	1.196	.107	(.081)	1.113	.233**	(.077)	1.263
SL gambling markets	.153	(.103)	1.165	.168	(.103)	1.183	−.208	(.119)	0.812	.131	(.102)	1.140
Population (per 1,000)	.603***	(.190)	1.828	.814**	(.257)	2.256	.386	(.199)	1.472	.548*	(.214)	1.730
SL population (per 1,000)	.451***	(.045)	1.570	.502***	(.052)	1.652	.522***	(.049)	1.685	.392***	(.047)	1.481
Disadvantage	.276***	(.027)	1.318	.322***	(.031)	1.379	.342***	(.029)	1.408	.248***	(.028)	1.281
Residential stability	.101***	(.031)	1.106	.110**	(.037)	1.117	.129***	(.034)	1.137	.143***	(.033)	1.154
Racial heterogeneity	.445***	(.093)	1.561	.423***	(.103)	1.527	.330***	(.099)	1.392	.482***	(.093)	1.620
Constant	−2.248	(.054)	—	−2.556	(.062)	—	−2.449	(.057)	—	−2.215	(.056)	—
Model Components												
Ln(α)	−.295	(0.078)	—	−.202	(.092)	—	−.295	(.090)	—	−.216	(.078)	—
Moran's I of residuals[a]	.065***	—	—	.062***	—	—	.058***	—	—	.056***	—	—

Note: Models estimated for census blocks with at least 20 residents (n = 13,164). SL = spatially lagged; Coef. = coefficient; *SE* = standard error; IRR = incident rate ratio. Robust standard errors are shown (Weesie 1999).

[a]Moran's I values shown were calculated for the standardized Pearson residuals using a first-order Queen spatial weights matrix and 999 permutations. Moran's I results were substantively similar for other spatial weights matrices.

***$p < .001$, **$p < .01$, *$p < .05$.

Table 3. Equality of Coefficients Tests Results.

Variables	Omnibus Test	Fall versus Winter	Fall versus Spring	Fall versus Summer	Winter versus Spring	Winter versus Summer	Spring versus Summer
High schools	9.58*	5.94*	5.26*	5.80*	*ns*	*ns*	*ns*
Higher education	8.28*	7.86**	*ns*	*ns*	*ns*	*ns*	*ns*
SL alcohol stores	11.12*	*ns*	*ns*	4.44*	*ns*	6.02*	8.83*

Note: All tests are based on models displayed in Table 2. All omnibus tests are based on three degrees of freedom. All pairwise tests are based on one degree of freedom. Omnibus tests were computed for only predictors statistically significantly linked to street robbery in Table 2. Pairwise tests were only estimated for variables with statistically significant omnibus tests. *ns* = not statistically significant.
***p < .001, **p < .01, *p < .05.

linked to statistically significantly higher street robbery counts during all seasons: (1) ATMs and banks, (2) corner stores, (3) fast-food restaurants, (4) parks, (5) subway stations, (6) narcotics markets, (7) prostitution markets, (8) SL check cashing stores, (9) SL corner stores, (10) SL fast-food restaurants, and (11) SL subway stations. For example, each additional ATM and/or bank in a census block linked to an expected street robbery count that was roughly 17.8 percent (fall), 30.0 percent (winter), 19.9 percent (spring), or 29.5 percent (summer) higher.

A total of 12 other predictors linked to statistically significantly higher street robbery during only some seasons: (1) bars, (2) check cashing stores, (3) drug treatment facilities, (4) high schools, (5) pawn shops, (6) public housing communities, (7) SL drug treatment centers, (8) SL high schools, (9) SL higher education institutions, (10) SL public housing communities, (11) SL narcotics markets, and (12) SL prostitution markets. For example, each bar in a census block was associated with 16.3 percent higher expected street robbery counts during the fall, but the effect was statistically indistinguishable from zero during the winter, spring, and summer.

Conversely, three predictors were statistically significantly but negatively linked to census block street robbery counts during only some seasons: (1) higher education institutions, (2) tourist sites, and (3) SL alcohol stores. For example, census blocks with a higher education institution had 42 percent lower street robbery counts during the winter and 25.8 percent lower street robbery counts during the summer, but the effect was statistically indistinguishable from zero during the fall and spring. These effects were contrary to our hypothesis that all facilities would link positively to street robbery regardless of season, given findings from previous studies (e.g., Bernasco and Block 2011).

"[T]he Difference Between 'Significant' and 'Not Significant' is not Itself Statistically Significant" (see Gelman and Stern 2006), so we now turn to the formal tests comparing the magnitudes of coefficients across seasons to test our hypothesis that facilities with usage patterns that vary across seasons due to their definitional purpose should have greater effects on crime during high-use seasons (see Table 3). The potentially criminogenic facilities examined in the present study did not consistently exhibit seasonal effects on street robbery as hypothesized. Only three predictors were statistically significantly different in magnitude across seasons: (1) high schools, (2) higher education institutions, and (3) SL alcohol stores.

First, the effect of high schools on street robbery during the fall was statistically significantly larger than the effects for winter, spring, and summer. This is the only finding that is consistent with our original hypotheses. In short, high schools have larger effects on street robbery when they are in session, particularly at the beginning of the year. Second, the equality of coefficient tests showed the higher education institutions effect was significantly smaller during the winter compared to the fall. While this finding is inconsistent with our original hypotheses, it makes sense within the context of our theoretical frame. Recall the effect of higher education institutions was negative in all models, but achieved statistical significance during only the winter and summer. Therefore, this difference coincides with when classes are out of session and the weather is colder relative to the start of a new school year or, stated differently, when university campuses become locations with minimal usage and high security. The positive effect of SL alcohol stores was also statistically significantly greater than the negative effects observed during fall, winter, or spring, but only the negative effect observed during the spring was significantly different from zero. Thus, it is difficult to derive theoretical meaning from this finding.

Finally, the sociodemographic control variables all positively linked to street robbery as expected from past research. Census blocks with greater residential populations in the immediate and nearby areas, more socioeconomic disadvantage, more residential mobility, and more racial heterogeneity were all predicted to have greater street robbery levels across all seasons.

Sensitivity Analyses

The results of the sensitivity analyses are summarized below but displayed in the Online Supplemental Material to conserve space. Modeling the spatial structure of the data with SL outcomes rather than SL predictors did not impact the results' substantive conclusions (tables 2 and 3 of Online Supplemental Material). Most spatially immediate facilities and sociodemographic control predictors remained positively linked to street robbery. Some predictors, however, had effects with different statistical significance patterns. High schools actually achieved statistical significance across all models in the alternative specification, but parks, public housing communities, subway stations, and tourist sites achieved statistical significance during fewer seasons. Nonetheless, the effect of high schools during the fall was still statistically significantly larger than the winter or summer. In terms of the study's primary research question, the substantive conclusions of the study were not impacted by modeling the data's spatial structure differently.

Reestimating the models for individual year outcomes also did not change the study's substantive conclusions regarding our primary research question. One difference for the individual year outcomes, however, was that while many potentially criminogenic facilities continued to be positively linked to street robbery, the significance patterns of many predictors were altered (table 4 of Online Supplemental Material). For example, narcotics markets were the only predictor that maintained its statistically significant link to street robbery across all (12) models. The general trend across the yearly seasonal models is that the coefficients were smaller and standard errors were larger, which suggests there was more noise in the data that ultimately produced fewer statistically significant effects.

Although we stress caution when interpreting their effects due to the large number of significance tests conducted, the equality of coefficient tests for the yearly outcome models produced two main findings in line with the previous conclusions drawn about the seasonality of potentially criminogenic places (table 5 of Online Supplemental Material). First, despite the different significance patterns in the yearly outcome models, the effects of potentially criminogenic places did not vary much across years. Pawn shops, public housing communities, and SL high schools each had two pairs of effects for the same season that were statistically significantly different across years, which would be indicative of the MTUP. If one was to interpret the importance of the effects of potentially criminogenic facilities based on their significance patterns outlined in the previous paragraph, then the conclusions one might draw about individual predictors would depend on the year examined, but the relatively minimal between-year differences in coefficient magnitude across years were not statistically meaningful (see Gelman and Stern 2006).

The second major finding of the yearly sensitivity tests was that the effects of potentially criminogenic facilities were still not found to be seasonal. Statistically significant differences across seasons observed for pawn shops, public housing communities, SL alcohol stores, and SL high schools were only observed in a single year. Thus, we have little confidence that these effects represent theoretically meaningful seasonal differences, albeit if our study had only been conducted for one year, we might have concluded so. It is important to further note, however, that the statistically significant differences for high schools between fall and the other seasons observed in both sets of models for three-year sum outcomes were not replicated in the yearly seasonal models. Overall, at least one takeaway lesson learned from these sensitivity analyses is that important findings from crime and place studies modeling sparse outcomes should be replicated across different jurisdiction and times.

Discussion

This study investigated whether or not the effects of some potentially criminogenic facilities and illicit markets on street robbery varied across seasons. Similar to past research, many potentially criminogenic facilities and illicit market linked to higher census block street robbery counts, but differences in the effects' magnitudes across seasons generally were not statistically significant. Overall, the present study arrived at the general conclusion that places with potentially criminogenic facilities where people are likely to be carrying cash consistently generate robbery opportunities despite changes in peoples' routine activity patterns across seasons. This conclusion is similar to studies that have looked at within-day spatial-temporal robbery patterns (Bernasco et al. 2017; Haberman and Ratcliffe 2015).

The lone exception was the immediate effect of high schools. High schools were the only facility with an effect that significantly varied across seasons as hypothesized (albeit not in the yearly seasonal models). Similar to past research, high schools generally linked to higher robbery levels (Bernasco and Block 2011; Bernasco et al. 2017; Groff and Lockwood 2014; Roman 2005), but the effect of high schools was statistically significantly larger during the fall. This finding may stem from the heightened activity and thus awareness of potential street robbery opportunities around high schools at the beginning of the school year. High schools were also the only facility to generate differential effects on within-day street robbery site selections in a past study (Bernasco et al. 2017). This may suggest that extremely abrupt changes in human activities, such as those that occur across seasonal and daily high school opening/closing times, are required to change street robbery opportunity structures and generate statistically detectable changes in street robbery levels. Thus, in reality, changes in human activity patterns do not change quickly enough in most situations to generate observable statistical differences in crime patterns.

The above explanation for high schools is still consistent with the fact that many facilities and illicit markets linked to higher street robbery across all seasons. In short, some places may still generate enough usage to facilitate street robbery opportunities even if usage decreases during some seasons. For example, people will need to access cash year-round, so they will frequent ATMs and banks regardless of the season. Patrons may want to finish their transactions more quickly and be less likely to stand around outside during seasons with poor weather, but they will still need to at least visit ATMs and banks year-round. Determined robbers may have to spend more time searching for targets during less busy seasons, but targets will eventually present themselves at places that are used, even at low levels, year-round. Given the difficulties in measuring a facilities' actual usage over different temporal scales, "how much" usage is necessary to generate street robbery opportunities remains unknown (see Haberman and Ratcliffe 2015: 478; Haberman et al. 2017: 562-63).

The present findings may also be explained by robbers' rational decision-making (Wright and Decker 1997). Perhaps robbers only search for targets in areas where they do not expect opportunities to vary seasonally. In other words, robbers may have decided that places with seasonally varying levels of targets are poor locations for robbery and choose to mostly focus on places with year-round opportunities. This explanation is effectively spatial-temporal displacement (see Repetto 1976) in which robbers seek out street robbery opportunities year-round but have simply adjusted to changes in routine activity patterns and chosen to focus on areas where human activity is relatively stable. Recall higher education institutions and tourist sites were statistically significantly associated with lower robbery levels in at least some models. In fact, the effect of higher education institutions in the winter was also statistically significantly smaller than the effect during the fall. It may be that both types of places exhibited a protective effect for street robbery simply due to the fact they are "bad" places to commit robberies during those seasons and robbers then decide to stay away the rest of the year as well.

Likewise, Bernasco and colleagues' (2017: 266) explanation that motivated robbers identify street robbery opportunities during their normal routine activities could also plausibly explain the present findings. Consistent with RAT, robbers in Philadelphia may just spend their time in areas with the places, such as narcotics markets, that consistently linked to higher street robbery. The present findings may say less about changes in the distribution of potential targets across seasons and more about the stability of offenders' activity spaces across seasons. Stated differently, Philadelphia robbers may just go to the same places year-round; thus, potentially criminogenic facilities do not have seasonal effects because they are not changing the spatial distribution of motivated offenders across seasons. The link between (changes in) the spatial distribution of motivated offenders and crime remains an understudied area that deserves further exploration.

Readers should keep in mind the study's limitations when considering its results. Perhaps the most important challenge facing crime and place research is the development of appropriate independent variables. Potentially criminogenic facilities and illicit markets derived from crime incident data serve as proxies for the complex human activity patterns that facilitate the convergence of motivated offenders and suitable targets lacking capable guardianship. The present study used the geographic locations of different facilities and illicit markets as proxy measures for these complex social dynamics. Future research should directly measure changes in these mechanisms across places in order to be able to develop more conclusive causal support for environmental criminology. For example, researchers may be able to use detailed sales data (Askey et al. 2017), geolocated social media data (Malleson and Andresen 2015), or even mobile phone tracking data to estimate human activity flows (see Haberman et al. 2017).

Astute readers will also recognize the commonly experienced modifiable areal unit problem and related MTUP. The present results could be sensitive to the spatial and temporal units used. The present results may also be unique to Philadelphia. External validity is always an empirical question that must be addressed via additional research (Taylor 1994), so studies using other spatial units, temporal scales, and locations are encouraged.

Related to the previous point, this study examined street robbery only, so the findings and their implications are not generalizable to other crime types. Environmental criminology's most important contribution, perhaps, is using science to understand crime patterns in order to guide more robust policy responses and applied science (Cullen 2011).Therefore, future research will need to study the spatial-temporal patterns of other crime types. For example, the social impacts of gun violence necessitate the need to understand and prevent it. The current paradigm for understanding and preventing gun violence is to view it as a group/gang problem stemming from “petty” personal beefs (Kennedy 2011). Perhaps, gun violence has stable spatial-temporal patterns because group/gang members have stable routine activity patterns or patterns that simply change according to population-wide changes in routine activities. Conversely, gun violence spatial-temporal patterns may change in unique ways if risky individuals have unique routine activity patterns such as frequenting certain types of places at certain times. These are all open empirical questions, but understanding gun violence’s spatial-temporal patterns at larger temporal scales may in return change how we think about this issue and contribute to the development of innovative responses to gun violence.

The spatial-temporal patterns of high-volume property crimes, such as burglary, theft from automobiles, or theft of automobiles, also provide viable opportunities for future research. Burglary is unique in that the target (i.e., place) does not move over time, but, of course, the occupants do. Burglaries may spike in residential areas during warmer seasons when people leave for vacations, whereas commercial areas may experience more burglaries in the winter if places closer earlier, given less pedestrian traffic. Of course, the holiday shopping season may drive additional dynamics. More similar to robbery, vehicles are located in different places at different times over the span of seasons. Seasonal changes in weather patterns may also change driver habits. For example, police departments constantly worry about the theft from and of vehicles in residential areas during the winter when residents leave them unlocked and running to allow them to heat up. Alternatively, vehicle crimes could concentrate in commercial areas during the warmer seasons as people leave their windows down and/or the car running (with air conditioning) when running into certain types of locations. Vehicle crime may also increase in places like parks or tourist areas as usage increases at these locations during the summer. In addition to the potential policy applications that accompany theoretically understanding spatial-temporal crime patterns, the identification of seasonal differences in the spatial predictors of crime for analogous but different crime types may suggest that offender target searchers are crime-specific. The importance of being *crime specific* versus *crime general* is an understudied concept in geographic criminology that needs further empirical consideration (Haberman 2017).

Nonetheless, an overarching theoretical contribution of this potential work would be how it informs the efficacy of different theoretical frameworks. It is unclear how the community criminology perspective (i.e., social disorganization, collective efficacy, or informal social control) can explain spatial and temporal crime patterns (for an overview of community criminology see Taylor 2015). Presumably, neighborhood social processes change slowly (over years not seasons) with changes in neighborhood composition and relational networks (Bursik and Grasmick 1999). Further, it is also unclear whether community criminology is a crime specific or crime general theory (see Haberman 2017). If different crime types have different spatial-temporal patterns that can be explained via environmental criminology mechanisms (see our points on improving the measurement of environmental criminology mechanisms above), then the utility of community criminology—at least as a standalone theory in its current form—may be questioned. In effect, studying spatial-temporal patterns of different crime types will provide a face validity test of crime and place theories' assumptions and logic and provide another needed way to contrast theories (see Taylor 2015).

Finally, researchers will have to continue to develop methods to best model the spatial-temporal patterns of rare crimes (also see Haberman et al. 2017). Environmental criminology theories tend to be crime specific (Clarke and Cornish 1985; Cornish and Clarke 1986; Haberman 2017). For example, hypotheses explaining the spatial-temporal distribution of street robbery would likely be different than those explaining residential burglary (albeit that is an empirical question as previously noted). Aggregating crime events to microplaces and temporal units results in sparse outcomes with less variance. If one focuses on the statistical significance of individual predictors, then which predictors were "important" in the present models would have sometimes been slightly different for each year (but see Gelman and Stern 2006). In many cases, researchers do not examine the same models across more than one year, so we do not know the sensitivity of past findings to the study year chosen. Previous null relationships among predictors and rare crime counts may have simply been the result of how studies' dependent variables were operationalized and the lack of signal in the data. Overall, this was less of an issue for the present study because our primary research question was whether or not there were seasonal differences in the magnitudes of the effects of different facilities, and the answer to that question ("not really") did not change across analytic decisions. Including time in geographic criminology is an important yet understudied area (Haberman et al. 2017; Ratcliffe 2010), so developing innovative techniques to study rare crimes will be vital in the future.

In sum, the present study argued that research had yet to test the complex changes in spatial crime patterns expected to occur across seasons according to CPT. The present study found some potentially criminogenic places linked to street robbery during some seasons, while others achieved statistical significance across all seasons. What was noticeable, even in a city with significant temperature and weather differences, was that the magnitudes of effects were rarely significantly different across seasons, suggesting that the effects of potentially criminogenic facilities and illicit markets are not seasonal.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Supplemental Material

Supplementary material for this article is available online.

Notes

1. Rotton and Cohn (2000) suggested the negative affect escape model could be incorporated into the routine activities explanation of the relationship between temperature and violence.
2. In the discussion that follows, we focus on facilities and illicit markets in which we have data on and can ultimately examine in the study that follows. Researchers with access to additional data may pose and test additional hypotheses regarding other types of facilities in the future.
3. One may hypothesize that facilities used year-round may still experience different usage across seasons. For example, patrons may frequent bars more when professional sports are in season. Since we did not have detailed usage data for the facilities/illicit markets included in our study and any specific hypotheses regarding these predictors' usage would be speculative, we decided to focus on just the two general hypotheses stated above that require less speculation to propose. If we find specific seasonal differences in the effects of the predictors believed to be in use year-round included in this study, the effects will be interpreted post hoc within that context, and future research using detailed usage data will have to test these interpretations more directly (e.g., see Askey et al. 2017).
4. It is recognized that some studies correlating weather and aggregate crime levels included analyses looking at seasonal spikes prior to estimating weather-crime correlations.

5. The Philadelphia Police Department (PPD) used a dual ranges address locator with a 20-feet offset (NAD 1983 State Plane Pennsylvania South FIPS 3702 Feet) to geocode the incident data provided. PPD has refined its geocoding process over nearly three decades and uses a series of street alias tables to consistently achieve high hit rates. A random subset of data were inspected by hand to ensure geocoding, and aggregation to census blocks was accurate. Check commands were built into the data-cleaning scripts to ensure proper incident counts were maintained during data cleaning.
6. Drug treatment centers were downloaded from the Pennsylvania Spatial Data Access website. Higher education institutions were downloaded from the U.S. Department of Education's Office of Postsecondary Education. Tourist sites were compiled from web searches of Visit Philadelphia and Trip Advisor. PPD provided data for all other facilities.
7. Alcohol stores captured state-owned wine and spirits stores and large beer distributors. These locations sell large quantities of alcohol, such as bottles of wine or spirits or cases or kegs of beer. Pennsylvania state liquor laws limit alcohol sales for off-site consumption to those locations. There are exceptions to these laws, and some bars or corner stores have obtained licenses to sell small quantities of alcohol for off-site consumption, but these locations were not identifiable in available data. Tourist sites captured Philadelphia's historical sites, museums and galleries, theaters, monuments and statues, and other landmarks and points of interest. Since 2011, Philadelphia and its neighboring counties have hosted at least 38 million visitors (Greater Philadelphia Tourism Marketing Corporation 2015), which demonstrates the magnitude of Philadelphia's tourist activity.
8. The facility data were represented as points and polygons. All point data were geocoded as outlined in footnote 5 with a 100 percent hit rate. Polygon data included four facilities that spanned large areas (i.e., high schools, higher education institutions, neighborhood parks, and public housing communities). Except for higher education institutions (campus boundaries were digitized by the authors), the facilities represented as polygons were digitized by the data provider. Since these places were never present more than once in a census block, they were simply intersected with census blocks and coded 1 = present and 0 = absent and identified with (dummy) above. Subway stops were also measured using a dummy variable because they are dispersed in space at single locations. The remaining facilities (points) were operationalized as counts and denoted (count) above.
9. These items were assigned to census blocks from the census tract file due to data availability.
10. Although the α value was less than the commonly used threshold of .7, we retained the measure, given the long history of operationalizing residential mobility this way in the literature.

11. Spatial error models are another method for modeling spatial data. These models build spatial dependence directly into the error term, thus accounting for the "spatial influence of unobserved (unmeasured) independent variables" (see Bernasco and Elffers 2010: 708). We did not estimate spatial error models for several reasons. First, we had a theoretical rationale for using spatially lagged predictors, which in return fully accounted for the spatial dependence in our data. As such, theory should underpin model building. Second, spatial error models are used less frequently in criminology, and the methods we used to address spatial dependence in this study are considered state of the art in the criminological literature. Third, to our knowledge, no conventional statistical packages estimate negative binomial spatial error models within the simultaneous framework necessary to answer our primary research question. Therefore, as these models become more widespread in criminology and beyond, that limitation may change and future research may consider further testing the sensitivity of crime and place statistical models by including spatial error terms.
12. We thank an anonymous reviewer for noting this point and, along with the editor, encouraging the sensitivity analyses.
13. The results were not sensitive to other spatial weights matrix specifications (e.g., 5 nearest neighbors, ¼ mile inverse distance, or 2nd-order queen).

References

Anderson, C. A. and K. M. DeNeve. 1992. "Temperature, Aggression, and the Negative Affect Escape Model." *Psychological Bulletin* 111:347-51.

Andresen, M. A. 2006. "Crime Measures and the Spatial Analysis of Criminal Activity." *British Journal of Criminology* 46:258-85.

Andresen, M. A. 2010. "Diurnal Movements and the Ambient Population: An Application to Municipal-level Crime Rate Calculations." *Canadian Journal of Criminology and Criminal Justice* 52:97-109.

Andresen, M. A. 2011. "The Ambient Population and Crime Analysis." *The Professional Geographer* 63:193-212.

Andresen, M. A. and G. W. Jenion. 2010. "Ambient Populations and the Calculation of Crime Rates and Risk." *Security Journal* 23:114-33.

Andresen, M. A. and N. Malleson. 2013. "Crime Seasonality and Its Variations across Space." *Applied Geography* 43:25-35.

Anselin, L. 1995. "Local Indicators of Spatial Association—LISA." *Geographical Analysis* 27:93-115.

Askey, A. P., R. B. Taylor, E. Groff, and A. Fingerhut. 2017. "Fast Food Restaurants and Convenience Stores: Using Sales Volume to Explain Crime Patterns in Seattle." *Crime & Delinquency*. doi: 10.1177/0011128717714792.

Baron, R. A. and P. A. Bell. 1976. "Aggression and Heat: The Influence of Ambient Temperature, Negative Affect, and a Cooling Drink on Physical Aggression." *Journal of Personality and Social Psychology* 33:245-55.

Baumer, E. and R. Wright. 1996. "Crime Seasonality and Serious Scholarship: A Comment on Farrell and Pease." *British Journal of Criminology* 36:579-81.

Bell, P. A. 1992. "In Defense of the Negative Affect Escape Model of Heat and Aggression." *Psychological Bulletin* 111:342-46.

Bernasco, W. and R. Block. 2011. "Robberies in Chicago: A Block-level Analysis of the Influence of Crime Generators, Crime Attractors, and Offender Anchor Points." *Journal of Research in Crime and Delinquency* 48:33-57.

Bernasco, W. and H. Elffers. 2010. "Statistical Analysis of Spatial Crime Data." Pp. 699-724 in *Handbook of Quantitative Criminology*, edited by A. R. Piquero and D. Weisburd. New York: Springer.

Bernasco, W., S. Ruiter, and R. Block. 2017. "Do Street Robbery Location Choices Vary over Time of Day or Day of Week? A Test in Chicago." *Journal of Research in Crime and Delinquency* 54:244-75.

Block, R. L. and C. B. Block. 2000. "The Bronx and Chicago: Street Robbery in the Environs of Rapid Transit Stations." Pp. 121-35 in *Analyzing Crime Patterns: Frontiers of Practice*, edited by V. Goldsmith, P. McGuire, J. Mellkopf, and T. Ross. Thousand Oaks, CA: Sage.

Block, R. L. and S. Davis. 1996. "The Environs of Rapid Transit Stations: A Focus for Street Crime or Just another Risky Place?" Pp. 145-84 in *Crime and Place*, edited by R. V. Clarke. Monsey, NY: Criminal Justice Press.

Braga, A. A., D. M. Hureau, and A. V. Papachristos. 2011. "The Relevance of Micro Places to Citywide Robbery Trends: A Longitudinal Analysis of Robbery Incidents at Street Corners and Block Faces in Boston." *Journal of Research in Crime and Delinquency* 48:7-32.

Braga, A. A., A. V. Papachristos, and D. M. Hureau. 2010. "The Concentration and Stability of Gun Violence at Micro Places in Boston, 1980-2008." *Journal of Quantitative Criminology* 26:33-53.

Braga, A. A., A. V. Papachristos, and D. M. Hureau. 2014. "The Effects of Hot Spots Policing on Crime: An Updated Systematic Review and Meta-analysis." *Justice Quarterly* 31:633-63.

Brantingham, P. L. and P. J. Brantingham. 1981. "Mobility, Notoriety, and Crime—A Study in the Crime Patterns of Urban Nodal Points." *Journal of Environmental Systems* 11:89-99.

Brantingham, P. J. and P. L. Brantingham. 1993. "Environment, Routine, and Situation: Toward a Pattern Theory of Crime." Pp. 27-54 in *Routine Activity and Rational Choice*, edited by R. V. Clarke and M. Felson. New Brunswick, NJ: Transaction.

Brantingham, P. L. and P. J. Brantingham. 1999. “A Theoretical Model of Crime Hot Spot Generation.” *Studies on Crime & Crime Prevention* 8:7-26.

Breetzke, G. D. and E. G. Cohn. 2012. “Seasonal Assault and Neighborhood Deprivation in South Africa: Some Preliminary Findings.” *Environment and Behavior* 44:641-67.

Brunsdon, C., J. Corcoran, G. Higgs, and A. Ware. 2009. “The Influence of Weather on Local Geographical Patterns of Police Calls for Service.” *Environment and Planning B: Planning and Design* 36:906-26.

Bursik, R. J., Jr., and H. G. Grasmick. 1999. *Neighborhoods & Crime: The Dimension of Effective Community Control*. Lanham, MD: Lexington Books.

Cameron, A. C. and P. K. Trivedi. 2013. *Regression Analysis of Count Data*. 2nd ed. New York: Cambridge University Press.

Ceccato, V. 2005. “Homicide in Sao Paulo, Brazil: Assessing Spatial-temporal and Weather Variations.” *Journal of Environmental Psychology* 25:307-21.

Chainey, S. and J. H. Ratcliffe. 2005. *GIS and Crime Mapping*. London, UK: Wiley.

Clarke, Ronald V. and D. B. Cornish. 1985. “Modeling Offender’s Decisions: A Framework for Research and Policy.” *Crime and Justice* 6:147-85.

Clarke, R. V. and J. E. Eck. 2005. *Crime Analysis for Problem Solvers*. Washington, DC: Center for Problem Oriented Policing.

Cohen, L. and M. Felson. 1979. “Social Change and Crime Rate Trends: A Routine Activity Approach.” *American Sociological Review* 44:588-608.

Cohn, E. G. 1990. “Weather and Crime.” *British Journal of Criminology* 30:51-64.

Cohn, E. G. and J. Rotton. 1997. “Assault as a Function of Time and Temperature: A Moderator-variable Time-series Analysis.” *Journal of Personality and Social Psychology* 72:1322-44.

Cohn, E. G. and J. Rotton. 2000. “Weather, Seasonal Trends and Property Crimes in Minneapolis, 1987–1988. A Moderator-variable Time-series Analysis of Routine Activities.” *Journal of Environmental Psychology* 20:257-72.

Cornish, Derek B. and R. V. Clarke. 1986. “Introduction.” Pp. 1-16 in *The Reasoning Criminal: Rational Choice Perspectives on Offending*, edited by D. B. Cornish and R. V. Clarke. New York: Springer-Verlag.

Cullen, F. T. 2011. “Beyond Adolescent-limited Criminology: Choosing Our Future—The American Society of Criminology 2013 Sutherland Address.” *Criminology* 49:287-330.

Falk, G. J. 1952. “The Influence of the Seasons on the Crime Rate.” *The Journal of Criminal Law, Criminology, and Police Science* 43:199-213.

Farrell, Graham, Andromachi Tseloni, Jen Mailley, and Nick Tilley. 2011. “The Crime Drop and the Security Hypothesis.” *Journal of Research in Crime and Delinquency* 48:147-75.

Felson, M. and M. Eckert. 2016. *Crime and Everyday Life*. 5th ed. Thousand Oaks, CA: Sage.

Field, S. 1992. "The Effect of Temperature on Crime." *British Journal of Criminology* 32:340-51.

Gelman, A. and H. Stern. 2006. "The Difference between 'Significant' and 'Not Significant' is not Itself Statistically Significant." *The American Statistician* 60: 328-31.

Gibbs, J. P. and W. T. Martin. 1962. "Urbanization, Technology, and the Division of Labor: International Patterns." *American Sociological Review* 27:667-77.

Goodell, R. 2012. *Official Playing Rules and Casebook of the National Football League*. New York: National Football League.

Greater Philadelphia Tourism Marketing Corporation. 2015. "Domestic Visits to Greater Philadelphia by Market Segment." Retrieved February 5, 2017 (http://files.visitphilly.com/Visitor%20Volume%201997-2015.pdf).

Groff, E. R. 2011. "Exploring 'Near': Characterizing the Spatial Extent of Drinking Place Influence on Crime." *Australian & New Zealand Journal of Criminology* 44:156-79.

Groff, E. R. and B. Lockwood. 2014. "Criminogenic Facilities and Crime across Street Segments in Philadelphia: Uncovering Evidence about the Spatial Extent of Facility Influence." *Journal of Research in Crime and Delinquency* 51:277-314.

Groff, E. R. and E. S. McCord. 2011. "The Role of Neighborhood Parks as Crime Generators." *Security Journal* 25:1-24.

Haberman, C. P. 2017. "Overlapping Hot Spots? Examination of the Spatial Heterogeneity of Hot Spots of Different Crime Type." *Criminology & Public Policy* 16: 633-60.

Haberman, C. P., E. R. Groff, and R. B. Taylor. 2013. "The Variable Impacts of Public Housing Community Proximity on Nearby Street Robberies." *Journal of Research in Crime and Delinquency* 50:163-88.

Haberman, C. P. and J. H. Ratcliffe. 2015. "Testing for Temporally Differentiated Relationships among Potentially Criminogenic Places and Census Block Street Robbery Counts." *Criminology* 53:457-83.

Haberman, C. P., E. T. Sorg, and J. H. Ratcliffe. 2017. "Assessing the Validity of the Law of Crime Concentration across Different Temporal Scales." *Journal of Quantitative Criminology* 33:547-67.

Hägerstrand, T. 1970. "What about People in Regional Science?" *Papers of the Regional Science Association* 24:6-21.

Harries, K. D. and S. J. Stadler. 1983. "Determinism Revisited Assault and Heat Stress in Dallas, 1980." *Environment and Behavior* 15:235-56.

Harries, K. D., S. J. Stadler, and R. T. Zdorkowski. 1984. "Seasonality and Assault: Explorations in Inter-neighborhood Variation, Dallas 1980." *Annals of the Association of American Geographers* 74:590-604.

Hawley, A. H. 1950. *Human Ecology: A Theory of Community Structure*. New York: The Ronald Press.

Heller, N. B. and R. E. Markland. 1970. “A Climatological Model for Forecasting the Demand for Police Service.” *Journal of Research in Crime and Delinquency* 7:167-76.

Hilbe, J. M. 2007. *Negative Binomial Regression*. Cambridge, UK: Cambridge University Press.

Hipp, J. R., P. J. Curran, K. A. Bollen, and D. J. Bauer. 2004. “Crimes of Opportunity or Crimes of Emotion? Testing Two Explanations of Seasonal Change in Crime.” *Social Forces* 82:1333-72.

Johnson, L. T. 2016. “Drug Markets, Travel Distance, and Violence: Testing a Typology.” *Crime & Delinquency* 62:1465-87.

Johnson, L. T. and J. H. Ratcliffe. 2013. “When Does a Drug Market Become a Drug Market? Finding the Boundaries of Illicit Event Concentrations.” Pp. 25-48 in *Crime Modeling and Mapping Using Geospatial Technologies*, edited by M. Leitner. New York: Springer.

Johnson, L. T., R. B. Taylor, and J. H. Ratcliffe. 2013. “Need Drugs, Will Travel? The Distances to Crime of Illegal Drug Buyers.” *Journal of Criminal Justice* 41:178-87.

Kennedy, D. M. 2011. *Don’t Shoot: One Man, A Street Fellowship, and the End of Violence in Inner-city America*. New York: Bloomsbury.

Kubrin, C. E., G. D. Squires, S. M. Graves, and G. C. Ousey. 2011. “Does Fringe Banking Exacerbate Neighborhood Crime Rates?” *Criminology & Public Policy* 10:437-66.

Lab, S. P. and J. D. Hirschel. 1988. “Climatological Conditions and Crime: The Forecast is . . . ?” *Justice Quarterly* 5:281-99.

Landau, S. F. and D. Fridman. 1993. “The Seasonality of Violent Crime: The Case of Robbery and Homicide in Israel.” *Journal of Research in Crime and Delinquency* 30:163-91.

Levine, N. 2015. *CrimeStat: A Spatial Statistics Program for the Analysis of Crime Incident Locations* [version 4.02]. Washington, DC: Ned Levine and Associates and the National Institute of Justice.

Linning, S. J. 2015. “Crime Seasonality and the Micro-spatial Patterns of Property Crime in Vancouver, BC and Ottawa, ON.” *Journal of Criminal Justice* 43:544-55.

Linning, S. J., M. A. Andresen, and P. J. Brantingham. 2016. “Crime Seasonality: Examining the Temporal Fluctuations of Property Crime in Cities with Varying Climates.” *International Journal of Offender Therapy and Comparative Criminology* 61(16):1-26.

Long, J. S. and J. Freese. 2006. *Regression Models for Categorical Dependent Variables Using Stata*. College Station, TX: Stata Press.

MacDonald, J. M. and P. K. Lattimore. 2010. “Count Models in Criminology.” Pp. 683-98 in *Handbook of Quantitative Criminology*, edited by A. R. Piquero and D. Weisburd. New Delhi, India: Springer.

Malleson, N. and M. A. Andresen. 2015. "Spatio-temporal Crime Hotspots and the Ambient Population." *Crime Science* 4:1-8.

Mares, D. 2013. "Climate Change and Crime: Monthly Temperature and Precipitation Anomalies and Crime Rates in St. Louis, MO 1990–2009." *Crime, Law and Social Change* 59:185-208.

McCord, E. S. and K. A. Houser. 2015. "Neighborhood Parks, Evidence of Guardianship, and Crime in Two Diverse US Cities." *Security Journal* 30(3):1-18.

McDowall, D., C. Loftin, and M. Pate. 2012. "Seasonal Cycles in Crime, and Their Variability." *Journal of Quantitative Criminology* 28:389-410.

Mears, D. P. 2007. "Towards Rational and Evidence-based Crime Policy." *Journal of Criminal Justice* 35:667-82.

Monk, K. M., J. A. Heinonen, and J. E. Eck. 2010. *Street Robbery*. Washington, DC: U.S. Department of Justice Office of Community Oriented Policing Services.

Osgood, D. W. 2000. "Poisson-based Regression Analysis of Aggregate Crime Rates." *Journal of Quantitative Criminology* 16:21-43.

Peng, C., S. Xueming, Y. Hongyong, and L. Dengsheng. 2011. "Assessing Temporal and Weather Influences on Property Crime in Beijing, China." *Crime, Law and Social Change* 55:1-13.

Quetelet, M. A. 1842. *A Treatise on Man and the Development of His Facilities*. Edinburgh, UK: W. and R. Chambers.

Ratcliffe, J. H. 2004. "Geocoding Crime and a First Estimate of a Minimum Acceptable Hit Rate." *International Journal of Geographical Information Science* 18:61-72.

Ratcliffe, J. H. 2010. "Crime Mapping: Spatial and Temporal Challenges." Pp. 5 in *Handbook of Quantitative Criminology*, edited by A. R. Piquero and D. Weisburd. New York: Springer.

Ratcliffe, J. H. 2012. "The Spatial Extent of Criminogenic Places: A Changepoint Regression of Violence around Bars." *Geographical Analysis* 44:302-20.

Repetto, T. A. 1976. "Crime Prevention and the Displacement Hypothesis." *Crime and Delinquency* 22:166-77.

Roman, C. G. 2005. "Routine Activities of Youth and Neighborhood Violence: Spatial Modelling of Place, Time, and Crime." Pp. 293-310 in *Geographic Information Systems and Crime Analysis*, edited by F. Wang. Hershey, PA: Idea Group.

Roncek, D. W. and R. Bell. 1981. "Bars, Blocks, and Crimes." *Journal of Environmental Systems* 11:35-47.

Roncek, D. W. and P. A. Maier. 1991. "Bars, Blocks, and Crime Revisited: Linking the Theory of Routine Activities to the Empiricism of 'Hot Spots'." *Criminology* 29:725-53.

Rotton, J. and E. G. Cohn. 1999. "Errors of Commission and Omission: Comment on Anderson and Anderson's (1998) 'Temperature and Aggression'." *Psychological Reports* 85:611-20.

Rotton, J. and E. G. Cohn. 2000. "Weather, Disorderly Conduct, and Assaults: From Social Contact to Social Avoidance." *Environment and Behavior* 32:651-73.

Rotton, J. and J. Frey. 1985. "Air Pollution, Weather, and Violent Crimes: Concomitant Time-series Analysis of Archival Data." *Journal of Personality and Social Psychology* 49:1207-20.

School District of Philadelphia. 2012. "Academic Calendar, 2011-2012." Retrieved February 5, 2017 (http://www.philasd.org/calendar/2011_2012/).

Sisti, D., M. B. L. Rocchi, A. Maccio, and A. Preti. 2012. "The Epidemiology of Homicide in Italy by Season, Day of the Week and Time of Day." *Medicine, Science, and the Law* 52:100-106.

Sorg, E. T. and R. B. Taylor. 2011. "Community Level Impacts of Temperature on Urban Street Robbery." *Journal of Criminal Justice* 39:463-70.

StataCorp. 2013. *Stata Statistical Software: Release 13*. College Station, TX: StataCorp.

Taniguchi, T., J. H. Ratcliffe, and R. B. Taylor. 2011. "Gang Set Space, Drug Markets, and Crime: Violent and Property Crime around Drug Corners in Camden." *Journal of Research in Crime and Delinquency* 48:327-63.

Taylor, R. B. 1994. *Research Methods in Criminal Justice*. New York: McGraw-Hill.

Taylor, R. B. 2015. *Community Criminology: Fundamentals of Spatial and Temporal Scaling, Ecological Indicators, and Selectivity Bias*. New York: NYU Press.

Thompson, S. K. and R. Gartner. 2014. "The Spatial Distribution and Social Context of Homicide in Toronto's Neighborhoods." *Journal of Research in Crime & Delinquency* 5:88-118.

Tompson, L. A. and K. J. Bowers. 2015. "Testing Time-sensitive Influences of Weather on Street Robbery." *Crime Science* 4:1-11.

Trenberth, K. E. 1983. "What Are the Seasons?" *Bulletin of the American Meteorological Society* 64:1276-82.

Tseloni, Andromachi, Graham Farrell, Rebecca Thompson, Emily Evans, and Nick Tilley. 2017. "Domestic Burglary Drop and the Security Hypothesis." *Crime Science* 6:1-16.

U.S. Census Bureau. 2010a. *2010 United States Census*. Washington, DC: U.S. Census Bureau.

U.S. Census Bureau. 2010b. *Standard Hierarchy of Census Geographic Entities*. Washington, DC: U.S. Census Bureau.

U.S. Census Bureau. 2011. *American Community Survey*. Washington, DC: U.S. Census Bureau.

Weesie, J. 1999. "Seemingly Unrelated Estimation and the Cluster-adjusted Sandwich Estimator." *Stata Technical Bulletin* 9:231-48.

Welsh, Brandon C., Gregory M. Zimmerman, and Steven N. Zane. 2017. "The Centrality of Theory in Modern Day Crime Prevention: Developments, Challenges, and Opportunities." *Justice Quarterly, Online First* 15(1):139-61.

Weisburd, D. 2015. "The Law of Crime Concentration and the Criminology of Place." *Criminology* 53:133-57.

Weisburd, D. L., S. Bushway, C. Lum, and S.-M. Yang. 2004. "Trajectories of Crime at Places: A Longitudinal Study of Street Segments in the City of Seattle." *Criminology* 42:283-321.

Weisburd, D. L., E. R. Groff, and S.-M. Yang. 2012. *The Criminology of Place: Street Segments and Our Understanding of the Crime Problem*. New York: Oxford University Press.

Wheeler, A. P. 2016. "Quantifying the Local and Spatial Effects of Alcohol Outlets on Crime." Retrieved March 9, 2018 from: https://ssrn.com/abstract=2869198 or http://dx.doi.org/10.2139/ssrn.2869198

Wheeler, A. P., R. E. Worden, and S. J. McLean. 2016. "Replicating Group-based Trajectory Models of Crime at Micro-places in Albany, NY." *Journal of Quantitative Criminology* 32:589-612.

White, H. 1982. "Maximum Likelihood Estimation of Misspecified Models." *Econometrica* 50:1-25.

Wright, R. T. and S. H. Decker. 1997. *Armed Robbers in Action: Stickups and Street Culture*. Boston, MA: Northeastern University Press.

Yan, Y. Y. 2004. "Seasonality of Property Crime in Hong Kong." *British Journal of Criminology* 44:276-83.

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