CRIMINOLOGY

TESTING FOR TEMPORALLY DIFFERENTIATED RELATIONSHIPS AMONG POTENTIALLY CRIMINOGENIC PLACES AND CENSUS BLOCK STREET ROBBERY COUNTS*

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This study examined street robbery patterns in Philadelphia, Pennsylvania, from the years 2009 to 2011 to determine whether the effects of potentially criminogenic places are different across different periods of the day. Census block (N = 13,164) street robbery counts across four periods (6:45 A.M. to 9:59 A.M., 10:00 A.M. to 4:29 P.M., 4:30 P.M. to 9:14 P.M., and 9:15 P.M. to 6:44 A.M.) were modeled with 12 different potentially criminogenic places, 3 measures of illicit markets, 4 compositional control variables, and spatially lagged versions of the 12 potentially criminogenic places and population using simultaneously estimated negative binomial regression models. Differences in the magnitudes of the parameter estimates across the time periods were assessed with Wald tests. Overall, the patterns across the four models were mostly consistent with the effects hypothesized based on the study's crime pattern theory and time-geography theoretical frame; yet differences in the magnitudes of the coefficients were less pronounced than hypothesized. Overall, the results provide moderate support for the crime pattern theory and time-geography explanation of spatial-temporal robbery patterns; however, numerous points are raised for future crime and place research.

An axiom of the crime and place literature is that certain types of places are important predictors of the spatial distribution of crime (P. L. Brantingham and P. J. Brantingham, 1999; P. J. Brantingham and P. L. Brantingham, 1991; Wilcox and Eck, 2011) and even can be used to forecast crime events (Caplan, Kennedy, and Miller, 2010). The link among certain types of places and higher crime levels has been empirically demonstrated for many different types of places, such as high schools, bars and taverns, convenience stores, public transportation stations, check-cashing stores, liquor stores, parks, and public housing communities (Bernasco and Block, 2011; Weisburd, Groff, and Yang, 2012). Whether by acting as a crime attractor or as a generator, the proclivity of criminogenic places to

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produce crime problems is also theorized to be a function of time (P. L. Brantingham and P. J. Brantingham, 1995; Felson and Boba, 2010). Aggregate human activity patterns exhibit natural temporal rhythms (Chapin, 1974; Cohen and Felson, 1979; Hawley, 1950). These natural rhythms influence when and where the basic elements of crime—motivated offenders and suitable targets lacking adequate guardianship—can converge during the course of a day (Felson, 2006). The purpose of the current study is to investigate whether the effects of potentially criminogenic facilities are measurably different across various times of the day.

THEORETICAL FRAMEWORK

CRIME PATTERN THEORY

Crime pattern theory describes the environmental backcloth (i.e., urban landscape) as a collection of nodes (i.e., places) connected to one another via pathways (i.e., the street network and other transportation modes) (P. L. Brantingham and P. J. Brantingham, 1993; P. J. Brantingham and P. L. Brantingham, 1993a, 1993b). The distribution of a city's land uses and arrangement of transportation pathways determines where and how people can travel through the city (Horton and Reynolds, 1971; Groff, Weisburd, and Morris, 2009; Kinney et al., 2008). Peoples' daily travel occurs within their activity spaces—or the places they visit routinely and the routes they take between those places (Horton and Reynolds, 1971; P. L. Brantingham and P. J. Brantingham, 1993).

By drawing from the routine activity approach (Cohen and Felson, 1979), crime pattern theory predicts crime will cluster along the most commonly traveled pathways and around particular nodes that create the greatest number of offender–target–inadequate guardianship convergences (P. J. Brantingham and P. L. Brantingham, 1993b). However, human activity patterns are not uniform throughout the duration of a day (Chapin, 1974; Felson, 2006; Felson and Boba, 2010; Felson and Poulsen, 2003). Human activities take place at locations within finite time periods because human activity is constrained by biological and social factors (Hägerstrand, 1970; Miller, 2005; Ratcliffe, 2006). For example, humans' biological need for sleep constrains our movement for long periods of time regularly each night. Human movement is limited also by coupling constraints or the need to engage with other individuals or organizations to participate in basic social and economic activities, such as the requirement to go to work, school, or the doctor's office at certain times. Finally, authority constraints are limitations put onto human movement by controlling individuals and groups (Hägerstrand, 1970; Miller, 2005; Ratcliffe, 2006).

In general, the regular rhythms observed in human activity patterns are mostly a result of diurnal and commerce patterns (Hawley, 1950; Pred, 1981) driven by coupling constraints (Chapin, 1974; Hägerstrand, 1970; Ratcliffe, 2006). During weekdays, adults tend to engage in paid employment or domestic chores during the day while children are at school. At the end of the business day, most people travel home. In the evening hours, people engage in discretionary activities, such as enjoying a few drinks with friends at a bar or restaurant; generally, however, time-use studies show the evening hours are mostly spent attending to housework, running errands, or watching television. The late-night and early-morning hours are spent sleeping to satisfy the body's natural need for sleep.

These temporal constraints suggest that, "As the relevant actors—victims, offenders, guardians, and place managers—adjust their relative densities over time and around specific places, the opportunities for crime shift and coagulate" (Ratcliffe, 2010: 15). It follows that if certain types of places concentrate crime opportunities by creating busy places, then the variation in human movement patterns during the course of a day is important for understanding the relationships among different types of places and crime (Cohen and Felson, 1979; Felson and Boba, 2010). Unfortunately, most studies linking potentially criminogenic places to elevated levels of crime across geographical units have been atemporal.

The handful of studies examining the spatial-temporal relationships among certain types of places and crime are outlined next. A study of automobile theft hot spots aggregated by police shift times in central Philadelphia found that the hot spots identified for each shift tended to encompass places where citizens were more likely to be visiting during that respective time. For example, one late-night hot spot (11:00 P.M. to 7:00 A.M.) overlapped with a popular nightlife area (Rengert, 1997). Similarly, maps and charts of data from Worcester, England, revealed that violence, harassment, and disorder concentrated in areas with pubs and clubs during the late-night hours when they were closing but began to spread out along the major transportation routes leading into residential areas even later into the nighttime and early morning hours (Bromley and Nelson, 2002). Roman (2005) found that Prince George's County, Maryland, census block group violent crime rates were positively linked to the number of retail places (an index of liquor license places, gas stations, and mini-markets) in a block across all times but that schools only increased violent crime rates during school commuting times and the school day. The density of off-premise alcohol outlets also has been linked to higher levels of domestic violence during weekend hours but not during weekday evenings (Roman and Reid, 2012). Conversely, both a study of casino versus noncasino hot spots in Reno, Nevada, and a study of casino buffer areas (2,000 ft) versus the rest of Reno found the temporal signatures of "casino crime" during the course of the day were not substantively different than the temporal signatures of "noncasino crime" (Barthe and Stitt, 2009a, 2009b).

CURRENT STUDY

Crime pattern theory hypothesizes that street robbery will concentrate near busy places because those places facilitate the convergences of motivated offenders and suitable targets lacking adequate guardianship. Time geography hypothesizes that places will not necessarily be busy at all times of the day because human activity patterns are constrained. Despite this theorizing on temporally differentiated links among particular types of places and crime levels across different times of the day, these temporally differentiated relationships have not been rigorously examined. Previous research examining the link between potentially criminogenic places and spatial-temporal crime patterns has been mostly descriptive (Barthe and Stitt, 2009a, 2009b; Bromley and Nelson, 2002; Rengert, 1997). Previous studies have used multivariate regression models (Roman, 2005; Roman and Reid, 2012) but did not employ formal tests to compare empirically the extent to which the effects of different places on crime vary by time of the day. The current study was designed to address these limitations.

First, American Time Use Survey (ATUS) data were analyzed with change point regression models to delineate time periods with distinct aggregate human activity patterns. The ATUS analysis identified four distinct macrolevel routine activity periods (Felson and Boba, 2010). These four periods were used to bound our street robbery dependent variable temporally. The street robbery dependent variable is discussed in detail next, but it was focused on during this study because of its practical advantages and alignment with our theoretical frame.

Second, microlevel hypotheses about how the study's predictors might link to census block street robbery levels differently across the four different times of the day were developed. The predictors investigated included measures of potentially criminogenic places, illicit markets, and census block composition. Although our set of potentially criminogenic places was guided by the literature and was comprehensive, it was limited by data availability and included 1) automated teller machines (ATMs) and banks, 2) alcohol stores, 3) bars, 4) check-cashing stores, 5) neighborhood corner stores, 6) drug-treatment centers, 7) high schools, 8) neighborhood parks, 9) subway stops, 10) fast-food restaurants, 11) pawn shops, and 12) public housing communities (which are included as independent variables). Similar to Bernasco and Block (2011), the second set of independent variables captured the presence of 13) narcotics markets, 14) prostitution markets, and 15) gambling markets. Although these activities are not the only possible ways people earn money "off the books" (Venkatesh, 2008), they are the predominant illegal markets likely to draw cash-carrying people (and, thus, potential robbery victims) to an area. The patrons of these markets also may be offenders who rob people in the areas close to the markets they frequent. Finally, consistent with a social disorganization theory perspective, we controlled for 16) census block population, 17) concentrated disadvantage, 18) residential mobility, and 19) racial heterogeneity (Bursik and Grasmick, 1993; Peterson and Krivo, 2010; Sampson, Raudenbush, and Earls, 1997; Shaw and McKay, 1942). The hypotheses and the logic supporting their derivation are outlined in detail later in this article. Finally, given their appropriateness for the research questions and data, simultaneous negative binomial regression models and equality of coefficient Wald tests were employed to test our hypotheses.

The remainder of this article is organized as follows. First, details on the process of identifying distinct periods of aggregate routine activity patterns with the ATUS data are outlined. Next, the hypotheses tested are listed in detail. Details on the data, measures, and analytical plan follow in the Methods section. Finally, the results, discussion, and limitations conclude the article.

IDENTIFYING DISTINCT DAILY PERIODS OF AGGREGATE ACTIVITY

The first step in testing for temporally differentiated links among potentially criminogenic places and street robbery was to identify distinct time periods of Americans' routine activities. To accomplish this, we analyzed the 2011 ATUS with change-point regression models. The ATUS is a nationally representative sample of when, where, and how Americans spend each minute of an average day (Bureau of Labor Statistics, 2011). Change-point regression models identify changes in trend data (Kim et al., 2000; Ratcliffe, 2012) (see the online supporting information[1] for more details on the ATUS data and change-point regression analyses). The change-point regression models were

1. Additional supporting information can be found in the listing for this article in the Wiley Online Library at http://onlinelibrary.wiley.com/doi/10.1111/crim.2015.53.issue-3/issuetoc.

estimated for four variables measuring the percentage of Americans engaged in activities at specific locations by minute of the day: 1) sleeping or activities occurring at the respondents' or family/friends' homes, 2) activities occurring at respondents' work or school locations, 3) activities occurring while traveling via private and public modes of transportation, and 4) activities occurring while respondents were in public locations. The change-point regressions objectively returned four time periods: 1) 6:45 A.M. to 9:59 A.M., 2) 10:00 A.M. to 4:29 P.M., 3) 4:30 P.M. to 9:14 P.M., and 4) 9:15 P.M. to 6:44 A.M.

Although the four time periods were derived empirically, they are intuitive within the environmental criminology and time-geography theoretical frame. The 6:45 A.M. to 9:59 A.M. time period is commonly thought of as the morning rush hour for the stereotypical "nine to five" workday (Chapin, 1974; Pred, 1981). Figure 1 shows the trend lines for the percentage of Americans in transit and at work or school gradually begin to increase between 6:45 A.M. and 9:59 A.M. The percentage of Americans at work or school levels off at the maximum of 34 percent by 10:00 A.M.

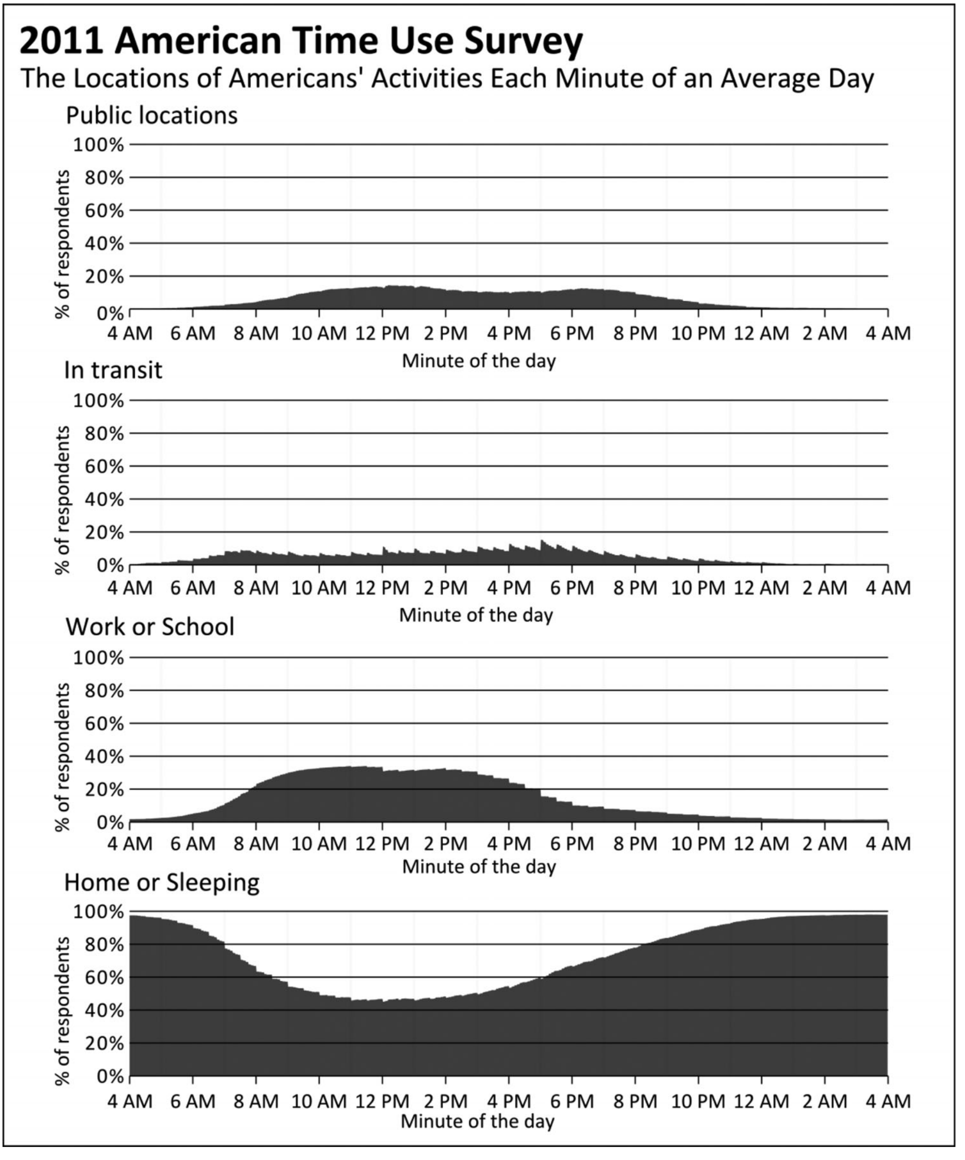
The second time frame, 10:00 A.M. to 4:29 P.M., predominantly captures the workday and school day (Chapin, 1974; Pred, 1981). By approximately noon, the percentage of Americans at home declines to about 45 percent (figure 1). On the other hand, the percentage of Americans engaged in non–work-related activities in public spaces spikes around the same time. This increase in routine activities away from home and work during this period is likely attributable to the workday lunch hour and to the routine activities of the unemployed, retired, or people who work during nighttime hours.

The third time period, 4:30 P.M. to 9:14 P.M., coincides with the evening commute and leisure activity hours. This time period corresponds to the dismissal times of the common 8-hour work day (based on the 40-hour workweek) established by the Fair Labor Standards Act of 1938 (Chapin, 1974; Hägerstrand, 1970; Pred, 1981). Recall that the ATUS survey includes Americans 15 years of age and older, and schools also generally dismiss students between 2:00 P.M. and 4:00 P.M. In figure 1, it is clear that the percentage of Americans participating in activities away from home experiences its second peak during this period. Overall, this period captures when large percentages of Americans are in public spaces (either in transit or engaging in leisure activities).

The final time period, 9:15 P.M. to 6:44 A.M., captures the late-night hours. The ATUS data in figure 1 shows nearly all Americans are at home during this time on an average day. Between 9:15 P.M. and 3:00 A.M., the percentage of Americans conducting activities in public places, which includes bars and restaurants, declines from approximately 4 percent to less than .5 percent where it remains for the rest of the survey period. Overall, the percentage of Americans at home between 9:15 P.M. and 6:44 A.M. ranges from approximately 84 percent to 98 percent (mean = 94 percent); thus, this time represents the part of the day when citizens are least likely to be in public.

To improve readability, we will refer to the time periods in more general terms throughout the remainder of the article. The 6:45 A.M. to 9:59 A.M. period will be referred to as the "morning." The 10:00 A.M. to 4:29 P.M. period will be referred to as the "daytime." The third time period, 4:30 P.M. to 9:14 P.M., will be referred to as the "evening." Finally, the term "late night" will be used to refer to the 9:15 P.M. to 6:44 A.M. period.

Figure 1. Locations of Americans' Activities Each Minute of an Average Day



NOTES: The percentage estimates were generated by using the survey weights provided in the ATUS and represent the percentage of American engaging in an activity at each location type for each minute of an average day during 2011. The estimates may not sum to 100 percent during a given minute because of missing data. Missing data represent less than .5 percent of the sample per minute.

HYPOTHESES

Based on crime pattern theory, previous studies, the ATUS data on macrolevel human activity patterns, and information on the hours of operation of specific places,[2] we hypothesized how each potentially criminogenic place would link differently to census block street robbery levels across each of the four time periods examined as well as how the magnitudes of the effects of the predictors would differ across each of the four time periods. These hypotheses follow (also see tables S.2 and S.3 of the online supporting information).

ATMS AND BANKS

Places with ATMs and banks are the quintessential place for potential robbers to find cash-carrying targets (St. Jean, 2007; Wright and Decker, 1997). Banks are open typically from 9:00 A.M. to 5:00 P.M., and ATMs are available 24 hours a day. Therefore, the ATMs and banks predictor is hypothesized to link to higher levels of street robbery across all four time periods. It is further hypothesized that ATMs and banks will have the greatest effect on street robbery counts during the daytime and evening hours compared with the other two time periods because people are most likely to use ATMs and banks when running errands and engaging in recreational activities during the core business day or evening hours. The effect of ATMs and banks on street robbery counts during the evening hours is hypothesized to be greater than during the daytime hours because the ATUS data suggest that most residents are likely to be engaged in public activities during this period.

ALCOHOL STORES

The alcohol stores variable captures state-owned wine and spirits stores and beer distributors that sell large quantities of beer for offsite consumption. Philadelphia's wine and spirits stores typically operate between 9:00 A.M. and 9:00 P.M. (Pennsylvania Liquor Code of 1951). Based on an Internet search, beer distributors in our data typically operate between 9:00 A.M. and approximately 7:00 P.M. to 10:00 P.M. It is hypothesized that alcohol stores will link significantly to higher street robbery levels only for the daytime and evening hours. Furthermore, the effect of alcohol stores on street robbery counts for the evening hours is hypothesized to be larger than that for the daytime (and all other) hours based on the notion that more people shop for alcohol during their evening recreational hours.

BARS

Although some bars serve light fare, the bars variable does not include places that function primarily as restaurants (even if they also have a bar area). Philadelphia liquor

2. We conducted Internet searches for each type of potentially criminogenic facility in our data set to identify common hours of operation for Philadelphia locations using Google and Yelp. We triangulated our findings using three search strategies. First, we searched "[location type] in Philadelphia" on Google. Second, we searched a random selection of 10 records using their names and locations from our data set on Google. Last, we searched each location type on Yelp while restricting our results to Philadelphia, Pennsylvania. All three search results returned consistent opening and closing times.

laws permit bars to serve alcohol between 7:00 A.M. and 2:00 A.M., but they must then be vacated by 2:30 A.M. (Pennsylvania Liquor Code of 1951). Most bars in Philadelphia open from the early afternoon until 2:30 A.M.; thus, bars are hypothesized to link to higher levels of street robbery for the daytime, evening, and late-night hours. Based on the ATUS data and the fact that bars host alcohol consumption well into the late-night hours, bars are hypothesized to have the largest effect on street robbery counts for the evening and late-night hours compared with the other two periods because these are likely their peak usage times. Even though the ATUS data suggest that most peoples' recreational activities take place during the evening hours, no difference in the effect of bars on street robbery counts between the evening and late-night hours is hypothesized given that bars are populated well into the late-night hours.

CHECK-CASHING STORES

Some Philadelphia check-cashing stores keep traditional business hours, such as 9:00 A.M. to 5:00 P.M. or 7:00 P.M. Others are open 24 hours a day. Because check-cashing places are open during all four periods, higher levels of street robbery are predicted across all four time periods. The effect is hypothesized to be the largest for the evening hours when most people have left work and are engaged in activities outside of their homes. No differences in the effects on the other three periods are hypothesized because check-cashing stores are open during those times, but business is presumed to be equally low.

CORNER STORES

In Philadelphia, corner stores located on blocks where most parcels are residential are only permitted to operate between 6:01 A.M. and 10:59 P.M. (City of Philadelphia §9-627, 2007). Corner stores sometimes violate this regulation by staying open later, and corner stores on commercial blocks can be open 24 hours a day. Thus, corner stores are hypothesized to link to higher levels of street robbery during all four periods. Corner stores are hypothesized to have the largest effect on census block street robbery counts for the evening hours when, as the ATUS data suggest, people are most likely to engage in public activities. The second largest effect is hypothesized during the late-night hours when corner stores become "staging areas" where youth go to hang out or show off (Anderson, 1999; Goffman, 2014). No difference is hypothesized between the morning and daytime effects.

DRUG-TREATMENT CENTERS

Outpatient drug-treatment centers in Philadelphia maintain standard business hours, 9:00 A.M. to 5:00 P.M., with minor fluctuations of opening and closing times. It is hypothesized that drug-treatment centers will link to higher levels of street robbery during the morning, daytime, and evening hours when they are open. The effects of drug-treatment centers on the morning, daytime, and evening hours should be larger than the hypothesized null effect for the late-night hours; however, if drug-treatment centers see most of their clients during the day, then the effect for the daytime period should be the largest. Drug-treatment centers are hypothesized to have equal effects during the morning and evening hours because patients are equally likely to be traveling to and from the centers during those times.

FAST-FOOD RESTAURANTS

The fast-food restaurant data include both national franchises and locally owned take-out restaurants. Fast-food restaurants are regulated by the same codes as corner stores and can operate only between 6:01 A.M. and 10:59 P.M. on predominantly residential street blocks (Philadelphia code § 9-627). And although it is hypothesized that fast-food restaurants link to higher levels of street robbery across all four periods, the effect is hypothesized to be largest for the daytime and evening hours relative to the other two periods because these hours correspond to peak eating and leisure times. The effect is hypothesized to be equal for the daytime and evening hours because both times are when public eating activities peak. It is not hypothesized to be different between the morning and late-night hours because both periods cover possible but not peak times people eat at restaurants.

HIGH SCHOOLS

The school day in Philadelphia spans from approximately 8:00 A.M. to 3:00 P.M., but this schedule can vary across schools (The School District of Philadelphia, 2014). High schools are hypothesized to contribute to the increase in morning and daytime street robbery counts that capture school commuting times and the school day. The effect of high schools on street robbery counts for the morning and daytime hours is hypothesized to be equal but greater than the other two time blocks when schools are closed.

NEIGHBORHOOD PARKS

Philadelphia neighborhood parks are open to the public nearly 24 hours a day, and many neighborhood parks do not have hours of operation signage or security fencing (Groff and McCord, 2011). However, it is unlikely that people use parks in the dark during the late-night hours. The ATUS data support that assertion. Therefore, neighborhood parks are hypothesized to have increased morning, daytime, and evening street robbery levels. Neighborhood parks are then hypothesized to have the greatest effect during the evening hours when people report (in the ATUS data) being engaged in activities away from home, such as recreational activities. The effect is hypothesized to be equal for the morning and daytime street robbery periods when it is presumed that people might use neighborhood parks but not necessarily at a higher level during either period.

PAWN SHOPS

Philadelphia pawn shops operate during normal business hours, 9:00 A.M. to 5:00 P.M., with some stores opening or closing a couple of hours earlier or later on some days. Pawn shops are then hypothesized to link to higher street robberies for only the morning, daytime, and evening hours when they are open. Pawn shops are hypothesized to have the greatest effect during the daytime hours when they are expected to do most of their business compared with the other periods. The effect is hypothesized to be equivalent during the morning and evening periods when pawn shops are predominantly open.

PUBLIC HOUSING COMMUNITIES

The link between public housing and street robbery could vary across communities (Haberman, Groff, and Taylor, 2013), but public housing communities are hypothesized to increase street robbery across all four time periods. The effect of public housing is hypothesized to be the largest during the evening hours when residents are most likely to engage in activities outside their home. No difference in the effect of public housing between the morning and daytime hours is hypothesized because both periods represent times when routine activities around public housing communities are likely; both effects are expected to be larger than that for the late-night hours when the ATUS data suggest activity will be minimal.

SUBWAY STOPS

The Southeastern Pennsylvania Transportation Authority operates two major subway lines in Philadelphia. These subway lines operate approximately between the hours of 5:00 A.M. and 1:00 A.M. (Southeastern Pennsylvania Transportation Authority, 2014). The ATUS survey suggests that Americans start commuting at approximately 6:00 A.M. through the evening. The average American is no longer in transit after 10:00 P.M. The subway stops predictor is hypothesized to impact all four outcomes, but the effect of subways on street robbery counts is hypothesized to be greatest for the evening hours when transit activities peak in the ATUS data. Because the subway is in operation for at least a portion of the time for the other outcomes and ATUS transit activity still occurs, the effect is hypothesized to be equal for those outcomes.

ILLICIT MARKETS

It is difficult to know when illegal markets are most active. Official police data may reflect police activity patterns or actual patronage. However, ethnographic studies have suggested that illicit markets operate across the entire day with participants working in shifts from early in the morning until late into the night (Bourgois, 1996; Goffman, 2014; Levitt and Venkatesh, 2000; Moskos, 2008; Venkatesh, 2008). Thus, the measures capturing narcotics, prostitution, and gambling markets are hypothesized to link to higher levels of street robbery across all four outcomes. Because narcotics use, prostitution solicitation, and gambling can be considered illegal forms of recreational activities, the effects of the three illicit markets on street robbery counts are then hypothesized to be greatest during the evening and late-night hours. It is hypothesized that there will not be any difference in the effects of the three illicit market measures between the morning and daytime hours when illicit markets could reasonably host activity, but there is no reason to expect one period is more active than the other.

DEMOGRAPHIC CONTROLS

All four demographic control variables are hypothesized to predict all four street robbery outcomes, but the demographic effects are hypothesized to be equivalent across the four street robbery outcomes because we are unaware of any theorizing that hypothesizes time-varying effects for the social disorganization mechanisms the demographic controls measure via proxy.

SPATIALLY LAGGED PREDICTORS

The spatially lagged potentially criminogenic places predictors are hypothesized to have the same relationships and differential temporal effects as the nonlagged potentially criminogenic places predictors for all four periods.

METHODS

UNIT OF ANALYSIS

Census blocks in Philadelphia, Pennsylvania, were the units of analysis for this study. Located in the northeastern region of the United States, Philadelphia's roughly 1.5 million residents make it the fifth largest city in the United States. Philadelphia is predominantly made up of Black and White residents (roughly 43 and 41 percent, respectively) with approximately 12 percent of Philadelphians identifying as Hispanic or Latino (U.S. Census Bureau, 2010a). The Philadelphia Police Department (PPD) is the fourth largest in the United States with more than 6,000 officers. Crime pattern theory emphasizes microlevel units of analysis. Census blocks are the smallest geographical unit used by the U.S. Census Bureau. In urban areas like Philadelphia, census blocks are typically bounded by a street segment on each side, but they also could be bounded by other features such as railways or bodies of water. The average census block in Philadelphia is .008 square miles, which is approximately the size of four American football fields (Goodell, 2012).

DEPENDENT VARIABLE

Philadelphia faces a significant robbery problem. Between 2009 and 2011, the average annual robbery rate in Philadelphia was approximately 560 robberies per 100,000 residents, whereas the national average annual rate was approximately 126 robberies per 100,000 residents (Federal Bureau of Investigation, 2009, 2010, 2011). The PPD provided geocoded street robbery incident data for the years 2009 to 2011. Street robberies for the current study are incidents that involved the taking of another's property through force or the threat of force by one or more offenders on a Philadelphia street (see Monk, Heinonen, and Eck, 2010). Street robbery incidents included armed (handguns, rifles, and cutting instruments) and unarmed robberies as well as purse snatchings. The street robbery data were geocoded with a 98.5 percent success rate (N = 17,918) (see Ratcliffe, 2004).

Studying street robbery has several advantages. First, focusing on a single crime type makes it easier to understand the theoretical mechanisms driving a crime problem (Clarke, 2008; Smith, Frazee, and Davison, 2000), and robbery closely aligns with our theoretical frame. Street robbery is a quintessential predatory crime, and city residents can only become victims while they are on city streets in the course of their routine activities. Robbery offenders have reported that they prefer specific types of locations that draw in many potential victims who are likely to be carrying cash (St. Jean, 2007; Wright and Decker, 1997); this finding has been demonstrated empirically (Bernasco and Block, 2009; Bernasco, Block, and Ruiter, 2013). From a methodological standpoint, robbery has a relatively high reporting rate and does not suffer from the type of temporal inaccuracies that plague property crimes that occur when a victim is absent, which decreases the temporal accuracy of crime data (Ratcliffe, 2000).

Census block street robbery 3-year sums (2009–2011) were computed for the four time periods outlined by the ATUS analysis (see Bernasco and Block, 2011). Univariate statistics for all four time periods are shown in table 1. Approximately 94 percent of census blocks did not experience a single robbery during the morning hours; the census blocks experienced a mean of .06 street robberies (range, 0 to 6; standard deviation [SD] = .28). During the daytime hours, the average census block experienced .23 street robberies (range, 0 to 14; SD = .62), but approximately 83 percent of census blocks did not experience a single street robbery during this period. Census block street robbery counts ranged from 0 to 11 with an overall mean of .27 (SD = .63) during the evening hours, and yet approximately 80 percent of census blocks did not experience any street robberies during this time period. During the late-night period, street robbery census block counts ranged from 0 to 14 (mean = .54, SD = 1.00), and approximately 66 percent of census blocks did not experience any street robberies during this period.

INDEPENDENT VARIABLES

The first set of independent variables measures potentially criminogenic places. The PPD's Crime Mapping and Analysis Unit provided the data set of all potentially criminogenic places except for drug-treatment centers. The drug-treatment facilities data were from the Pennsylvania Department of Health and were downloaded from the Pennsylvania Spatial Data Access website (http://www.pasda.psu.edu/; Pennsylvania Department of Health, 2012). Google Maps was used to confirm each place's location and to ensure that its classification was correct. The data represent all known places of each type rather than just places known by police to be criminogenic. Census block counts were used for the 12 predictors that captured potentially criminogenic places discussed in the Hypotheses section. Next, census block incident counts of narcotics distribution, prostitution solicitation, or illegal gambling from the PPD's incident database were used to capture the three illicit markets, respectively. Finally, 2010 U.S. Census data were used to control for census block demographic composition (U.S. Census Bureau, 2010b).[3] Census block population data include counts of each resident. Although residential population counts are limited in their ability to capture transient populations (Andresen, 2006; Bernasco and Block, 2011), these population counts were expected to provide a reasonable baseline measure of population with the potentially criminogenic facilities variables hypothesized to capture changes in population resulting from aggregate routine activity patterns. Next, a principal components analysis of five census variables guided the creation of concentrated disadvantage and residential mobility indices.[4] The concentrated disadvantage index is the average of the standardized values of items that loaded on the first factor: 1) percentage

3. The 2010 U.S. Census did not contain measures of percentage of families in poverty, median household income, and educational attainment at the block level. Thus, those measures were aggregated to the census block level based on the 2010 American Community Survey's 5-year estimates at the census tract level.

4. A principal components analysis was performed. An inspection of scree plots and eigenvalues suggested a two-factor solution. The Cronbach's αs for the disadvantage index = .90 and for the residential mobility index = .40. We recognize the residential stability Cronbach's α is less than the commonly accepted .70 threshold, but given the results of principal components analysis and the precedent in the literature to measure residential mobility by using these two indicators, we opted to include the measure.

Table 1. Univariate Statistics for Study Variables

Variable	Minimum	Maximum	Median	Mean	SD
Dependent Variables: Robbery Counts[a]					
Morning hours (6:45 A.M. to 9:59 A.M.)	.00	6.00	.00	.06	.28
Daytime hours (10:00 A.M. to 4:29 P.M.)	.00	14.00	.00	.23	.62
Evening hours (4:30 P.M. to 9:14 P.M.)	.00	11.00	.00	.27	.63
Late-night hours (9:15 P.M. to 6:44 A.M.)	.00	14.00	.00	.54	1.00
Independent Variables					
ATMs and banks[b]	.00	9.00	.00	.06	.32
Alcohol stores[b]	.00	2.00	.00	.01	.09
Bars[b]	.00	6.00	.00	.04	.23
Check-cashing stores[b]	.00	3.00	.00	.01	.11
Corner stores[b]	.00	3.00	.00	.08	.30
Drug-treatment centers[b]	.00	4.00	.00	.01	.09
Fast-food restaurants[b]	.00	11.00	.00	.13	.49
High schools[b]	.00	2.00	.00	.01	.08
Neighborhood parks[b]	.00	2.00	.00	.01	.09
Pawn shops[b]	.00	2.00	.00	.00	.04
Public housing communities[b]	.00	2.00	.00	.02	.14
Subway stops[b]	.00	3.00	.00	.01	.08
Gambling markets[c]	.00	8.00	.00	.02	.20
Narcotics markets[c]	.00	131.00	.00	1.05	4.43
Prostitution markets[c]	.00	100.00	.00	.16	2.45
Spatially Lagged Independent Variables[d]					
Lagged ATMs and banks	.00	1.00	.29	.00	.45
Lagged alcohol stores	.00	1.00	.06	.00	.23
Lagged bars	.00	1.00	.18	.00	.39
Lagged check-cashing stores	.00	1.00	.07	.00	.26
Lagged corner stores	.00	1.00	.36	.00	.48
Lagged drug-treatment centers	.00	1.00	.04	.00	.19
Lagged fast-food restaurants	.00	1.00	.49	.00	.50
Lagged high schools	.00	1.00	.07	.00	.25
Lagged neighborhood parks	.00	1.00	.12	.00	.33
Lagged pawn shops	.00	1.00	.01	.00	.11
Lagged public housing communities	.00	1.00	.05	.00	.21
Lagged subway stops	.00	1.00	.05	.00	.22
Control Variables					
Population	20.00	4535.00	98.00	115.12	102.98
Lagged population[e]	.00	899.00	103.35	94.89	55.14
Concentrated disadvantage index	–2.48	2.41	.08	.09	.87
Residential mobility index	–1.13	3.66	.02	.12	.67
Racial heterogeneity	.00	.79	.30	.33	.22

[a] All dependent variables are census block street robbery counts ($N = 13{,}164$).
[b] Census block counts of each type of place.
[c] Census block incident counts of each type of illicit market crime.
[d] All spatially lagged independent variables are dummy variables capturing the presence versus nonpresence of each type of place.
[e] Queen contiguity weighted average.
ABBREVIATION: SD = standard deviation.

SOURCE: Data from the Philadelphia Police Department, 2010 United States Census Block Estimates.

of residents 25 years of age or older without a high-school degree, 2) median income (reverse scored, i.e., multiplied by negative one), and 3) percentage of families in poverty. Higher scores on the concentrated disadvantage index indicate that a census block is more disadvantaged. The residential mobility index is the average of the standardized values of two items that loaded onto the second factor: 1) the percentage of renter-occupied housing units and 2) the percentage of residents who moved in the last year. Higher scores on the residential mobility index indicate a census block has a less stable residential population. Racial heterogeneity is measured by using one minus the sum of the squared proportions of five race categories: 1) White, 2) Black, 3) Hispanic, 4) Asian, and 5) all other races. The racial heterogeneity measure is mathematically bounded from .00 to .80 with higher values indicating more racially heterogeneous census blocks (see Blau, 1977; Chainey and Ratcliffe, 2005; Gibbs and Martin, 1962).

SPATIAL EFFECTS

All four outcome measures exhibited spatial autocorrelation.[5] Spatially autocorrelated residuals produce inefficient estimates in regression models (Anselin, 1988). We follow the lead of Bernasco and Block (2011) and enter spatially lagged versions of our potentially criminogenic facilities variables to model the observed spatial dependence in census block street robbery counts (Anselin et al., 2000; Elffers, 2003). The theoretical foundation for this stems from research that shows potentially criminogenic places influence crime levels in the surrounding area over short distances (Groff, 2011; Groff and Lockwood, 2014; Ratcliffe, 2012). Spatially lagged effects are captured by using indicator variables measuring the presence versus non-presence of each of the potentially criminogenic facilities (i.e., "1" vs. "0") in the census blocks adjacent to each focal census block (i.e., queen contiguity). Univariate statistics for these measures are shown in table 1.[6]

ANALYSIS PLAN

Stata 13's *nbreg* and *suest* commands (StataCorp., College Station, TX) were used to estimate four negative binomial regression models simultaneously. We then estimated Wald tests by comparing the equality of coefficients across our four models with Stata 13's *test* command. Negative binomial regression models are appropriate for discrete count-dependent variables with overdispersion (i.e., a variance greater than its mean). These models account for overdispersion by incorporating both a mean and a variance parameter into the model (Osgood, 2000). Likelihood-ratio tests and diagnostic graphs confirmed

5. Spatial autocorrelation in the four dependent variables was tested using a Global Moran's I test in GeoDa 1.6.5. The Moran's I tests were conducted on only a census block with 20 or more residents. A distance-based spatial weights matrix using a 5,280 threshold was employed. Significance tests were based on 999 permutations. The Moran's I test results are as follows: 1) 6:45 A.M. to 9:59 A.M. ($I = 0.017$, $p < .001$), 2) 10:00 A.M. to 4:29 P.M. ($I = 0.036$, $p < .001$), 3) 4:30 P.M. to 9:14 P.M. ($I = 0.043$, $p < .001$), and 4) 9:15 P.M. to 6:44 A.M. ($I = 0.070$, $p < .001$). The results of the Moran's I values only varied by a couple hundredths or thousandths when a queen contiguity or k-nearest-neighbor matrices of order 4–6 were employed.

6. We also explored models using spatially lagged illicit market and compositional control measures, but these models had obvious signs of collinearity among the predictors. Both variance inflation factor scores were greater than 10, and the direction and significance of various predictors' coefficients were unintuitive or changed across models.

that negative binomial models fit the data better than Poisson count models (Long and Freese, 2006, Ch. 8).

Estimating separate negative binomial models for correlated outcomes from the same data set results in stochastically dependent parameter estimates. Therefore, Stata's *suest* command was used to provide parameter estimates for the models for each of the four outcomes by using a combined (co)variance matrix. With the combined (co)variance matrix, the models' parameter estimates are efficient and Stata's *test* command can compute appropriate Wald tests for the hypothesized differences in parameter estimates (Weesie, 1999). A global Wald test was first computed to determine whether any significant differences exist across any of the four coefficients. If a difference were found, then five pairwise comparisons were estimated to identify differences between specific pairs of coefficients.

To control for compositional effects, we restricted the analysis to only census blocks with at least 20 residents (N = 13,164). This decision was made to replicate in part Bernasco and Block's (2011) atemporal study of census block street robbery counts in Chicago, Illinois. After restricting the analysis to census blocks with at least 20 residents, 14,588 street robberies (of 17,918) remained in the analysis across the four time periods. We assessed collinearity by using variance inflation factor (VIF) scores. VIF scores were calculated prior to the simultaneous estimation. The max VIF score was 3.73, and the mean VIF score was 1.40. We assessed spatial autocorrelation in the Pearson residuals by using a Global Moran's I test with multiple spatial weights matrices in GeoDa 1.6.5. The Moran's I tests were conducted on only census blocks with 20 or more residents. A distance-based spatial weights matrix with a 5,280 threshold was employed, but the Moran's I differed only by a few hundredths of a decimal when a queen contiguity or k-nearest-neighbors matrices of the order 4–6 were employed.[7] Incident rate ratios (IRRs) also are displayed because they are easy to interpret. IRR are obtained by exponentiating the model coefficients. The IRR can then be converted to percentage increases or decreases for every one-unit increase in a predictor by multiplying the difference between the IRR and one by 100 where positive values indicate a percentage increase and negative values indicate a percentage decrease (Long and Freese, 2006).

RESULTS

SIMULTANEOUS NEGATIVE BINOMIAL REGRESSION MODELS

The results from the simultaneous negative binomial regression models are displayed in table 2. Six potentially criminogenic facilities were hypothesized to increase street robbery counts across all four time periods (ATMs and banks, check-cashing stores, corner stores, fast-food restaurants, public housing communities, and subway stations). Recall the same effects were hypothesized for the spatially lagged versions of the predictors. Of those six, only ATMs and banks, corner stores, and fast-food restaurants were actually associated with significantly[8] higher street robbery counts across all four time periods. Likewise, the spatially lagged effects of corner stores and fast-food restaurants were also associated with higher street robbery counts across all four time periods, but the spatially

7. The results were not sensitive to using different spatial weights matrices.
8. All effects discussed in the Results section are statistically significant at the $p < .05$ level or better unless otherwise noted.

Table 2. Simultaneous Negative Binomial Regression Results for Philadelphia Census Blocks

	Model A: Morning			Model B: Daytime			Model C: Evening			Model D: Late Night		
Variable	***b***	**(SE)**	**IRR**	***b***	**(SE)**	**IRR**	***b***	**(SE)**	**IRR**	***b***	**(SE)**	**IRR**
Constant	–3.604***	(.114)	.027	–2.469***	(.064)	.085	–2.338***	(.060)	.096	–1.622***	(.047)	.197
ATMs and banks	.191*	(.095)	1.210	.296***	(.064)	1.344	.243***	(.053)	1.275	.180***	(.049)	1.198
Alcohol stores	–.609	(.449)	.544	.071	(.145)	1.073	–.076	(.137)	.927	–.045	(.116)	.956
Bars	.070	(.155)	1.072	.144	(.088)	1.155	.016	(.083)	1.016	.113	(.060)	1.120
Check-cashing stores	.074	(.209)	1.077	.271*	(.114)	1.311	.242*	(.106)	1.274	.296**	(.098)	1.344
Corner stores	.367***	(.090)	1.443	.254***	(.058)	1.290	.224***	(.056)	1.251	.231***	(.042)	1.260
Drug-treatment centers	.413	(.246)	1.512	.316*	(.158)	1.372	.430***	(.110)	1.537	.162	(.112)	1.175
Fast-food restaurants	.115*	(.058)	1.122	.155***	(.035)	1.167	.141***	(.034)	1.151	.138***	(.031)	1.148
High schools	.600	(.349)	1.823	.727***	(.180)	2.069	.756***	(.195)	2.129	.466**	(.153)	1.593
Neighborhood parks	.618*	(.301)	1.855	.572**	(.181)	1.772	.356*	(.156)	1.428	.258	(.137)	1.294
Pawn shops	.739	(.939)	2.095	.850**	(.322)	2.339	.432	(.241)	1.540	.219	(.244)	1.244
Public housing communities	.211	(.237)	1.235	–.010	(.168)	.990	.187	(.155)	1.206	.029	(.123)	1.030
Subway stops	.504	(.321)	1.656	.686**	(.247)	1.985	.818***	(.219)	2.266	.689***	(.160)	1.992
Gambling markets	.185	(.114)	1.204	.176*	(.082)	1.193	.144	(.079)	1.154	.144*	(.067)	1.155
Narcotics markets	.015***	(.004)	1.015	.015***	(.003)	1.015	.013***	(.002)	1.013	.014***	(.002)	1.015
Prostitution markets	.026***	(.007)	1.026	.018***	(.004)	1.018	.019***	(.004)	1.019	.022***	(.004)	1.022
Population (/100)	.105*	(.042)	1.111	.066**	(.024)	1.068	.119***	(.027)	1.126	.113***	(.024)	1.120
Concentrated disadvantage	.400***	(.044)	1.492	.398***	(.027)	1.489	.287***	(.026)	1.332	.274***	(.020)	1.316
Residential mobility	.002	(.057)	1.002	.060	(.034)	1.061	.071*	(.032)	1.074	.190***	(.025)	1.209
Racial heterogeneity	–.066	(.174)	.936	.257*	(.101)	1.293	.624***	(.094)	1.866	.533***	(.071)	1.704
Lagged ATMs & banks	.265***	(.082)	1.303	.200***	(.047)	1.222	.081	(.045)	1.084	.037	(.035)	1.038
Lagged alcohol stores	.160	(.132)	1.174	.088	(.082)	1.092	–.054	(.079)	0.948	–.004	(.060)	.996
Lagged bars	–.010	(.100)	.990	.146**	(.055)	1.157	.087	(.051)	1.091	.163***	(.039)	1.178
Lagged check-cashing stores	.144	(.117)	1.154	.305***	(.063)	1.357	.207***	(.063)	1.230	.239***	(.050)	1.271
Lagged corner stores	.332***	(.079)	1.393	.211***	(.046)	1.235	.232***	(.043)	1.261	.240***	(.032)	1.271
Lagged drug-treatment centers	–.067	(.181)	.936	.307***	(.093)	1.360	.046	(.090)	1.047	.130	(.071)	1.139
Lagged fast-food restaurants	.220**	(.075)	1.246	.111**	(.043)	1.118	.157***	(.040)	1.170	.130***	(.030)	1.139
Lagged high schools	.424***	(.123)	1.528	.162*	(.080)	1.176	.129	(.074)	1.137	.134**	(.054)	1.143
Lagged neighborhood parks	.128	(.102)	1.137	.171**	(.060)	1.187	.142**	(.056)	1.153	.156***	(.043)	1.169
Lagged pawn shops	.229	(.219)	1.257	.328*	(.145)	1.389	.032	(.137)	1.032	.042	(.129)	1.043
Lagged public housing	.326*	(.166)	1.385	.221*	(.107)	1.248	.163	(.111)	1.177	.169*	(.084)	1.184
Lagged subway stops	.349**	(.140)	1.418	.522***	(.087)	1.685	.475***	(.079)	1.608	.311***	(.065)	1.365
Lagged population (/100)	.002	(.072)	1.002	.127***	(0037)	1.136	.124***	(.036)	1.132	.143***	(.030)	1.153
Global Parameters												
Lnalpha		.126			–.163			–.094			–.227	
Moran's *I*		.007			.019			.028			.042	

NOTES: $N = 13{,}164$ census blocks. Robust standard errors are shown (Weesie, 1999).
ABBREVIATIONS: b = beta coefficient; SE = standard error.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

lagged effects of ATMs and banks were only associated with higher street robbery counts during the morning and daytime hours.

The remaining three potentially criminogenic facilities hypothesized to increase street robbery counts across all four time periods exhibited unique patterns. The spatially immediate effects of check-cashing stores and subway stations linked to higher street robbery counts during only three of four time periods. The immediate and spatially lagged effects of check-cashing stores did not achieve significance during the morning hours. The spatially immediate effect of subway stations did not achieve significance during the morning hours, whereas the spatially lagged effects of the subway stations achieved significance during all four periods. Finally, the spatially immediate effect of public housing did not achieve statistical significance in any of the four time periods; however, the spatially lagged measure of public housing was associated with higher street robbery counts during the morning, daytime, and late-night hours.

The final six potentially criminogenic facilities were hypothesized to increase street robbery counts only during certain time periods. The spatially immediate and lagged effects of alcohol stores failed to reach significance across any time periods. The spatially immediate effect of bars also did not achieve significance during any time period; however, the presence of a bar in an adjacent census block linked to higher street robbery counts during the daytime and late-night hours. As (mostly) hypothesized, both the immediate and spatially lagged effects of drug-treatment centers increased street robbery counts during the daytime hours, and the spatially immediate (but not lagged) effects of drug-treatment centers was positive during the evening hours. In stark contrast to our hypotheses, the spatially immediate effect of high schools was positive during the daytime, evening, and late-night hours and the spatially lagged effect of high schools was positive during the morning, daytime, and late-night hours. The immediate effect of neighborhood parks was significant during all time periods except the late-night hours as hypothesized, and the spatially lagged effect of parks was significant during the late-night hours. Pawn shops were associated with higher street robbery counts in the immediate and adjacent census blocks only during the daytime hours.

The illicit market variables were also associated with higher street robbery counts. All three types of illicit markets were hypothesized to increase street robbery levels across all four time periods yet the results did not support these hypotheses completely. Narcotics distribution and prostitution solicitation incidents were both associated with higher robbery counts across all four time periods, but gambling incidents related to higher street robbery counts only during the daytime and late-night hours.

The census block composition variables were hypothesized to increase robbery counts across all four time periods. As hypothesized, census blocks with more residents and higher levels of concentrated disadvantage had higher street robbery counts during all four time periods. The spatially lagged effect of population was also associated with street robbery counts during the daytime, evening, and late-night hours. Contrary to our hypotheses, higher levels of residential mobility or racial heterogeneity only resulted in higher street robbery levels during the evening and late-night hours.

EQUALITY OF COEFFICIENTS WALD TESTS

Table 3 displays the equality of coefficient Wald test results. The spatially immediate effect of only one potentially criminogenic facility was found to differ across the four time periods. The effect of pawn shops on expected census block street robbery counts for the daytime hours was larger than the effect for the late-night hours.

Table 3. Equality of Coefficients Wald Tests Chi-Square Values for Effects with Significant Omnibus Tests

Variable	Omnibus Test	Morning Versus Daytime	Morning Versus Evening	Morning Versus Late Night	Daytime Versus Evening	Daytime Versus Late Night	Evening Versus Late Night
Pawn shops	11.59**	n.s.	n.s.	n.s.	n.s.	6.61**	n.s.
Population	7.86*	n.s.	n.s.	n.s.	6.05**	6.30**	n.s.
Concentrated disadvantage	22.72***	n.s.	5.40*	7.31***	11.63***	17.62***	n.s.
Residential mobility	22.64***	n.s.	n.s.	9.94**	n.s.	12.47***	12.16***
Racial heterogeneity	20.22***	n.s.	13.51***	11.04***	9.18**	6.28*	n.s.
Lagged ATMs and banks	15.29**	n.s.	4.43*	7.46**	4.50*	10.17***	n.s.
Lagged drug-treatment centers	8.60*	3.90*	n.s.	n.s.	6.68**	n.s.	n.s.
Lagged subway stations	7.99*	n.s.	n.s.	n.s.	n.s.	6.61**	4.53*

NOTES: $N = 13{,}164$. All tests are based on models displayed in table 2. All omnibus tests are based on 3 degrees of freedom. All pairwise tests are based on 1 degree of freedom. Pairwise tests were estimated only for variables with statistically significant omnibus tests.
ABBREVIATION: n.s. = not statistically significant.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

The magnitudes of three spatially lagged effects of potentially criminogenic facilities also were found to differ across the four time periods. The effects of spatially lagged ATMs and banks on street robbery counts were larger during both the morning and daytime hours than both during the evening and late-night hours. The effect of the presence of a drug-treatment center in an adjacent census block on street robbery counts was larger in the daytime hours compared with the morning and evening hours. Finally, the spatially lagged effects of subway stations on street robbery counts during both the daytime and evening hours were larger than the effect during the late-night hours.

Contrary to our hypotheses, differences in the magnitudes of the census block composition effects also were observed across the four time periods. The effects of population on street robbery counts for the evening and the late-night hours were significantly larger than population's effect for the daytime hours. Furthermore, the effects of the concentrated disadvantage index on street robbery counts for the morning and daytime hours were found to be larger than the effects for the evening and late-night hours. The effect of residential mobility on street robbery counts was larger during the late-night hours than during the morning, daytime, and evening hours. Finally, the racial heterogeneity effects on street robbery counts for both the evening and late-night hours were larger than the racial heterogeneity effects for both the morning and daytime hours.

DISCUSSION

The results provide moderate support for the integrated environmental criminology and time-geography theoretical frame studied. Explanations for why some places linked to higher levels of census block street robbery levels across different times of the day and for why the magnitudes of some of those effects differed across different times of the day are provided here. The article then concludes with a discussion of the limitations this study faced.

First, some potentially criminogenic facilities are open and likely in use for most of the day. Because those potentially criminogenic facilities have steady usage patterns, they facilitate street robbery opportunities in the immediate and surrounding areas across all four time periods. That dynamic likely explains why corner stores and fast-food restaurants linked to higher levels of street robbery in the immediate and adjacent areas across all four time periods.

Second, some potentially criminogenic facilities are open for most of the day but are not necessarily in use at all times. Those places linked to higher levels of street robbery during their peak usage times. This was likely the case for check-cashing stores and neighborhood parks. Most check-cashing stores are open for at least part of each of the four time periods, but use of these stores likely does not increase enough to facilitate street robbery opportunities until later in the day, evening, or night once people have at least been to work to receive their checks or need money for errands or recreational activities. Parks also are open 24 hours a day but are likely only used during the times when people are engaged in recreational activities.[9] In other words, being "open" is not

9. Of course, this makes it difficult to interpret the fact that the spatially lagged effect of parks was significant in the late-night hours model unless people are robbed walking home from parks when everybody stops using them at the beginning of the late-night hours.

sufficient for some places to facilitate street robbery because they experience relatively little usage during some times.

This explanation is supported by the fact that drug-treatment centers and pawn shops have specific opening and usage hours and are linked to high levels of street robbery only during those times. For example, drug-treatment centers increased census block street robbery counts during the daytime and evening hours when clients would typically be traveling to and from them. Likewise, despite pawn shops technically being open during a fraction of the morning and evening hours, they likely do most of their business during the daytime, which is when they were associated with street robbery.

A third group of places may be open and in use during a wide range of times, but their unique nature and usage patterns may impact how guardianship is generated. The significance patterns for ATMs and banks, subway stations, public housing communities, and bars exemplify this dynamic. For example, the effects for ATMs and banks might be observed because they are used all day, but robbers are more likely to wait for patrons to leave the safety of place managers and guardians when banks are open or victims may only be comfortable walking away from ATMs and banks during the morning and daytime hours. The observed effects for subway stations may be explained by a similar dynamic. During the morning hours, large numbers of riders converge on neighborhood-based stations or leave central business district stations together. As a result, guardianship levels are higher around stations and robbers must find opportunities in the surrounding areas. Later in the day, robbers can identify targets on trains or exiting stations and rob them wherever guardianship levels are low enough. Likewise, public housing communities only increased street robberies in the surrounding areas where residents are no longer under the protective watch of place managers and guardianship systems such as closed-circuit television cameras (which are common around Philadelphia public housing communities) and during the morning, daytime, and late-night hours when guardianship is likely lower in the surrounding areas. Finally, robbers may target bar patrons in nearby areas that are outside the view of bar staff and patrons during the daytime and late-night hours when people are generally least likely to be on the streets in the course of their routine activities.

Finally, the findings for the immediate and spatially lagged effects of high schools demonstrate that potentially criminogenic facilities may facilitate street robbery opportunities when open and in use, but some places may also facilitate street robbery opportunities during "unofficial" usage times as well. For example, the spatially lagged effects of high schools for the morning hours during school arrival and the spatially immediate effect of high schools for the daytime hours encompassing school dismissal times are likely driven by students robbing each other or being targeted by nonstudents as they travel to and from school. These explanations make sense if guardianship is lower in the surrounding areas during the morning commute or if students capitalize on opportunities they learn about in school right after dismissal. Furthermore, the after-school fight where something is stolen would ultimately be coded as a street robbery. Our work with crime analysts from the PPD anecdotally suggests this occurrence is somewhat common.

Conversely, it is difficult to develop an explanation for why high schools increased census block street robbery counts in the immediate area well after schools closed, but this finding may be explained by how high schools are used outside school hours. First, high schools can serve as staging areas (Anderson, 1999), and residents who use these spaces for other activities, such as pickup basketball games, outside school hours may create robbery opportunities. Second, activities held after school hours, such as sporting events or community meetings, could increase robbery opportunities in the area. Third, high schools may just be good places for robbers to wait for targets to walk by during the evening hours because they create large uninhabited areas with low guardianship and many escape routes. These mechanisms also may explain the spatially lagged effect of high schools during the evening and late-night hours.

The equality of coefficients results were less pronounced than hypothesized but consistent with the integrated environmental criminology and time-geography theoretical frame. The potentially criminogenic facilities that were found to differ across the four time periods can likely be attributed to two explanations: 1) stark differences in usage at particular times and 2) high levels of guardianship when places are open.

Pawn shops, subway stations, and drug-treatment centers are a few of the potentially criminogenic places with the starkest differences in usage patterns across the day. The fact that pawn shops impacted street robbery more during the daytime hours than the late-night hours likely is because these businesses are open during those times. Similarly, the larger effects for lagged subway stations during the daytime and evening hours compared with the late-night hours can likely be attributed to the fact that Philadelphia subways close around midnight. Finally, it is possible that drug-treatment centers see most of their clients during the daytime, which is why they exerted the greatest effect on nearby census blocks during the daytime hours than the morning and evening hours when either business has not picked up or has ended for the day.

The finding that the lagged ATMs and banks effect was larger during the daytime hours than the evening and late-night hours seems most compatible with a place management and guardianship explanation. Often, banks are located in commercial areas. ATMs that are not inside banks are located in or attached to businesses. As a result, the immediate areas of ATMs and banks experience high guardianship levels during the day. By contrast, if the streets in adjacent areas are residential, then they are likely to be sparsely populated during the day and offenders may be more likely to target patrons in nearby areas where guardianship is lower.

The compositional predictors were entered into the model as proxy control variables for the social processes from social disorganization theory or its variants that have explained differences in crime patterns across neighborhoods, but those effects were not expected to be different across the day. In contrast, it is possible that these measures are proxies for social processes that are important for the integrated environmental criminology and time-geography theoretical frame examined. The larger effect for concentrated disadvantage during the morning and daytime hours compared with the evening and late-night hours might be observed because many people are on the street rather than at work during the day in disadvantaged census blocks and this facilitates more robbery opportunities (Felson and Boba, 2010). The residential mobility predictor might be larger during the late-night hours compared with the other periods because it facilitates anonymity during the times when suspicious offenders might otherwise draw the most attention. In other words, from the morning through the evening hours it is possible for outsiders, who may be potential robbers, to travel anywhere in the city and not draw too much attention. However, in census blocks with greater residential stability, outsiders could attract more attention during the late-night hours when it is less common for people to be hanging out in public. If anonymity is higher in census blocks with greater residential mobility, then the local community may be less able to regulate that area during the late-night hours when it is most important. A similar dynamic also may explain why the effect of racial heterogeneity mattered more during the evening and late-night hours than the morning and daytime hours.

The findings and discussion need to be considered within the context of this study's limitations. First, the complex dynamic that the number of people using certain places is changing during the course of the day and impacting the convergences of motivated offenders and suitable targets lacking guardianship was not measured directly. Although we derived our hypotheses from theory, the literature, the ATUS data, and each type of place's hours of operation, it could be argued that the usage of places could be measured more directly as well. Future researchers with appropriate funding could directly measure the number of people in an area, the extent of guardianship, and other theoretically important constructs to refine the hypotheses and measures employed in this study. It is possible that additional data on how people use different places across the course of the day may lead to different hypotheses and findings. Those data also should be collected for a wider range of potentially criminogenic facilities than is examined here. For example, Bernasco and Block (2011) found barber shops, salons, and general merchandise stores were related to street robberies, but we lacked data on those facilities. Overall, the strongest support for the theoretical frame tested in this study would use direct measures of the theoretical mechanisms explored and the mechanisms from rival theories to test which theoretical frame has the most empirical support (Taylor, 2011, discusses the importance of directly measuring and empirically comparing alternative theoretical mechanisms; Reynald, 2009, demonstrates the importance of directly measuring environmental criminology mechanisms).

The results also may be sensitive to the spatial or temporal units employed. Although census blocks are the smallest unit in which data were available to control for compositional effects (e.g., see Eck and Weisburd, 1995; Groff, Weisburd, and Yang, 2010; Weisburd, Groff, and Yang, 2012;), they do not necessarily reflect the social reality of American cities. Other microunits, such as street blocks, may be more theoretically appropriate for capturing urban social processes (Taylor, 1997). Likewise, although the four temporal bounds were derived objectively and empirically, there may not be agreement among scholars on whether these are the appropriate times to study. Perhaps other scholars would argue for finer or wider time blocks. Other time periods may be theoretically important in other contexts. Scholars also might study temporal crime problems by day of the week, week of the month or year, or month of the year in the future.

Despite these limitations, the current study found moderate support for the integrated environmental criminology and time-geography theory framing this study. Future research can address the limitations of the current study and rule out alternative theoretical explanations by using longitudinal, multicity studies to provide more conclusive support. Nonetheless, the current study supports a provisional conclusion. Temporal patterns of human behavior are important for understanding spatial crime patterns, and time should be considered a vital parameter in the crime and place research agenda.

REFERENCES

Anderson, Elijah. 1999. *Code of the Street: Decency, Violence, and the Moral Life of the Inner City*. New York: Norton.

Andresen, Martin A. 2006. Crime measures and the spatial analysis of criminal activity. *British Journal of Criminology* 46:258–85.

Anselin, Luc. 1988. *Spatial Econometrics: Methods and Models*. Dordrecht, the Netherlands: Kluwer Academic Press.

Anselin, Luc, Jacqueline Cohen, David Cook, Wilpen Gorr, and George Tita. 2000. Spatial analyses of crime. *Criminal Justice: Measurement and Analysis of Crime and Justice* 4:213–62.

Barthe, Emmanuel, and B. Grant Stitt. 2009a. Impact of casinos on criminogenic patterns. *Police Practice & Research* 10:255–69.

Barthe, Emmanuel, and B. Grant Stitt. 2009b. Temporal distribrutions of crime and disorder in casino and non-casino zones. *Journal of Gambling Studies* 25:139–52.

Bernasco, Wim, and Richard Block. 2009. Where offenders choose to attack: A discrete choice model of robberies in Chicago. *Criminology* 47:93–130.

Bernasco, Wim, and Richard 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, Wim, Richard Block, and Stijn Ruiter. 2013. Go where the money is: Modeling street robbers' location choices. *Journal of Economic Geography* 13:119–43.

Blau, Peter M. 1977. *Inequality and Heterogeneity: A Primitive Theory of Social Structure*. New York: Free Press.

Bourgois, Philippe. 1996. *In Search of Respect: Selling Crack in El Barrio*. New York: Cambridge University Press.

Brantingham, Patricia L., and Paul J. Brantingham. 1993. Nodes, paths, and edges: Consideration on the complexity of crime and the physical environment. *Journal of Environmental Psychology* 13:3–28.

Brantingham, Patricia L., and Paul J. Brantingham. 1995. Criminality of place: Crime generators and crime attractors. *European Journal of Criminal Policy and Research* 3:5–26.

Brantingham, Patricia L., and Paul J. Brantingham. 1999. A theoretical model of crime hot spot generation. *Studies on Crime and Crime Prevention* 8:7–26.

Brantingham, Paul J., and Patricia L. Brantingham. 1991. Notes on the geometry of crime. In *Environmental Criminology*, eds. Paul J. Brantingham and Patricia L. Brantingham. Prospect Heights, IL: Waveland Press.

Brantingham, Paul J., and Patricia L. Brantingham. 1993a. Criminality of place: Crime generators and crime attractors. *European Journal of Criminal Policy and Research* 3:1-26.

Brantingham, Paul J., and Patricia L. Brantingham. 1993b. Environment, routine, and situation: Toward a pattern theory of crime. In *Routine Activity and Rational Choice*, eds. Ronald. V. Clarke and Marcus Felson. New Brunswick, NJ: Transaction.

Bromley, Rosemary D. F., and Amanda L. Nelson. 2002. Alcohol-related crime and disorder across urban space and time: Evidence from a British city. *Geoforum* 33:239–54.

Bureau of Labor Statistics. 2011. *American Time Use Survey*. Washington, DC: Bureau of Labor Statistics.

Bursik, Robert J., and Harold Grasmick. 1993. *Neighborhoods and Crime: The Dimensions of Effective Community Control*. New York: Lexington.

Caplan, Joel M., Leslie M. Kennedy, and Joel Miller. 2010. Risk terrain modeling: Brokering criminological theory and GIS methods for crime forecasting. *Justice Quarterly* 28:1–22.

Chainey, Spencer, and Jerry H. Ratcliffe. 2005. *GIS and Crime Mapping*. London, U.K.: Wiley.

Chapin, F. Stuart. 1974. *Human Activity Patterns in the City; Things People Do in Time and in Space*. New York: Wiley.

City of Philadelphia. 2007. Commecial Establishments on Residential Blockfaces. §9-627.

Clarke, Ronald V. 2008. Situational crime prevention. In *Environmental Criminology and Crime Analysis*, eds. Richard Wortley and Lorraine Mazerolle. Portland, OR: Willan.

Cohen, Lawrence, and Marcus Felson. 1979. Social change and crime rate trends: A routine activity approach. *American Sociological Review* 44:588–608.

Eck, John E., and David L. Weisburd. 1995. Crime places in crime theory. In *Crime and Place*, eds. John E. Eck and David L. Weisburd. Monsey, NY: Criminal Justice Press.

Elffers, Henk. 2003. Analysing neighbourhood influence in criminology. *Statistica Neerlandica* 57:347–67.

Federal Bureau of Investigation. 2009. *Uniform Crime Reports*. Washington, DC: U.S. Department of Justice.

Federal Bureau of Investigation. 2010. *Uniform Crime Reports*. Washington, DC: U.S. Department of Justice.

Federal Bureau of Investigation. 2011. *Uniform Crime Reports*. Washington, DC: U.S. Department of Justice.

Felson, Marcus. 2006. *Crime and Nature*. Thousand Oaks, CA: Sage.

Felson, Marcus, and Rachel L. Boba. 2010. *Crime and Everyday Life*, 4th ed. Thousand Oaks, CA: Sage.

Felson, Marcus, and Erika Poulsen. 2003. Simple indicators of crime by time of day. *International Journal of Forecasting* 19:595–601.

Gibbs, Jack P., and Walter T. Martin. 1962. Urbanization, technology, and the division of labor: International patterns. *American Sociological Review* 27:667–77.

Goffman, Alice. 2014. *On the Run: Fugitive Life in an American City*. Chicago, IL: University of Chicago Press.

Goodell, Roger. 2012. *Official playing rules and casebook of the National Football League*. New York: National Football League.

Groff, Elizabeth R. 2011. Exploring ”near”: Characterizing the spatial extent of drinking place influence on crime. *Australian and New Zealand Journal of Criminology* 44:156–79.

Groff, Elizabeth R., and Brian 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, Elizabeth R., and Eric S. McCord. 2011. The role of neighborhood parks as crime generators. *Security Journal* 25:1–24.

Groff, Elizabeth R., David L. Weisburd, and Nancy A. Morris. 2009. Where the action is at places: Examining spatio-temporal patterns of juvenile crime at places using tracjectory analysis in GIS. In *Putting Crime in its Place*, eds. David L. Weisburd, Wim Bernasco, and Gerben J. N. Bruinsma. New York: Springer.

Groff, Elizabeth R., David L. Weisburd, and Sue-Ming Yang. 2010. Is it important to examine crime trends at a local ”micro” level? A longitudinal analysis of street to street variability in crime trajectories. *Journal of Quantitative Criminology* 26:7–32.

Haberman, Cory P., Elizabeth R. Groff, and Ralph 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.

Hägerstrand, Torsten. 1970. What about people in regional science? *Papers of the Regional Science Association* 24:6–21.

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

Horton, Frank E., and David R. Reynolds. 1971. Effects of urban spatial structure on individual behavior. *Economic Geography* 47:36–48.

Kim, Hyune-Ju, Michael P. Fay, Eric J. Feuer, and Douglas N. Midthune. 2000. Permutation tests for joinpoint regression with applications to cancer rates. *Statistics in Medicine* (19):335–51.

Kinney, J. Bryan, Patricia L. Brantingham, Kathryn Wuschke, Michael G. Kirk, and Paul J. Brantingham. 2008. Crime attactors, generators, and detractors: Land use and urban crime opportunities. *Built Environment* 34:62–74.

Levitt, Steven D., and Sudhir Alladi Venkatesh. 2000. An economic analysis of a drug-selling gang's finances. *Quarterly Journal of Economics* 115:755–89.

Long, J. Scott, and Jeremy Freese. 2006. *Regression Models for Categorical Dependent Variables Using Stata*, 2nd ed. College Station, TX: Stata Press.

Miller, Harvey J. 2005. Necessary space-time conditions for human interaction. *Environment and Planning B: Planning and Design* 32:381–401.

Monk, Khadija M., Justin A. Heinonen, and John E. Eck. 2010. *Street Robbery. Vol. 59, Problem-Oriented Guides for Police Problem-Specific Guides Series*. Washington, DC: U.S. Department of Justice Office of Community Oriented Policing Services.

Moskos, Peter 2008. *Cop in the Hood: My Year Policing Baltimore's Eastern District*. Princeton, NJ: Princeton University Press.

Osgood, D. Wayne. 2000. Poisson-based regression analysis of aggregate crime rates. *Journal of Quantitative Criminology* 16:21–43.

Pennsylvania Department of Health. 2012. *Drug Alcohol Treatment Facilities*. Harrisburg: Pennsylvania Spatial Data Access.

Pennsylvania Liquor Code of 1951. 1951. 47 P.S. §1-101 et. seq.

Peterson, Ruth D., and Lauren J. Krivo. 2010. *Divergent Social Worlds: Neighborhood Crime and the Racial-Spatial Divide*. New York: Russell Sage Foundation.

Pred, Allan. 1981. Production, family, and free-time projects: A time-geographic perspective on the individual and societal changes in nineteenth-century U.S. cities. *Journal of Historical Geography* 7:3–36.

Ratcliffe, Jerry H. 2000. Aoristic analysis: The spatial interpretation of unspecific temporal events. *International Journal of Geographical Information Science* 14:669–79.

Ratcliffe, Jerry H. 2004. Geocoding crime and a first estimate of a minimum acceptable hit rate. *International Journal of Geographical Information Science* 18:61–72.

Ratcliffe, Jerry H. 2006. A temporal constraint theory to explain opportunity-based spatial offending patterns. *Journal of Research in Crime and Delinquency* 43:261–91.

Ratcliffe, Jerry H. 2010. Crime mapping: Spatial and temporal challenges. In *Handbook of Quantitative Criminology*, eds. Alex R. Piquero and David L. Weisburd. New York: Springer.

Ratcliffe, Jerry H. 2012. The spatial extent of criminogenic places: A changepoint regression of violence around bars. *Geographical Analysis* 44:302–20.

Rengert, George F. 1997. Auto theft in central Philadelphia. In *Policing for Prevention: Reducing Crime*, *Public Intoxication and Injury*, ed. Ross Homel. Mosney, NY: Criminal Justice Press.

Reynald, Danielle M. 2009. Guardianship in action: Developing a new tool for measurement. *Crime Prevention and Community Safety* 11:1–20.

Roman, Caterina G. 2005. Routine activities of youth and neighborhood violence: Spatial modelling of place, time, and crime. In *Geographic Information Systems and Crime Analysis*, ed. Fahui Wang. Hershey, PA: Idea Group.

Roman, Caterina G., and Shannon E. Reid. 2012. Assessing the relationship between alcohol outlets and domestic violence: Routine activities and the neighborhood environment. *Violence and Victims* 27:811–28.

Sampson, Robert J., Stephen W. Raudenbush, and Felton Earls. 1997. Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science* 277:918–24.

Shaw, Clifford R., and Henry D. McKay. 1942. *Juvenile Delinquency and Urban Areas: A Study of Delinquency in Relation to Differential Characteristics of Local Communities in American Cities*. Chicago, IL: The University of Chicago Press.

Smith, William R., Sharon Glave Frazee, and Elizabeth L. Davison. 2000. Furthering the integration of routine activity and social disorganization theories: Small units of analysis and the study of street robbery as a diffusion process. *Criminology* 38:489–523.

Southeastern Pennsylvania Transportation Authority. 2014. Southeastern Pennsylvania Transportation Authority Schedules. http://www.septa.org/schedules/.

St. Jean, Peter K. B. 2007. *Pockets of Crime: Broken Windows, Collective Efficacy, and the Criminal Point of View*. Chicago, IL: The University of Chicago Press.

Taylor, Ralph B. 1997. Order and disorder of streetblocks and neighborhoods: Ecology, microecology and the systemic model of social organization. *Journal of Research in Crime and Delinquency* 34:113–5.

Taylor, Ralph B. 2011. Communities and crime theories: Construct validation deficits, a paucity of comparisons, and a Boudon–Coleman metamodel resolution. *In Measuring Crime and Criminality: Advances in Criminological Theory*, ed. John M. MacDonald. New Brunswick, NJ: Transaction.

The School District of Philadelphia. 2014. Home page. http://www.phila.k12.pa.us/.

U.S. Census Bureau. 2010a. *Interactive Population Map*. Washington, DC: U.S. Census Bureau.

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

Venkatesh, Sudhir Alladi. 2008. *Off the Books: The Underground Economy of the Urban Poor*. Chicago, IL: First Harvard University Press.

Weesie, Jeroen. 1999. Seemingly unrelated estimation and the cluster-adjusted sandwich estimator. *Stata Technical Bulletin* 52:34–47.

Weisburd, David L., Elizabeth R. Groff, and Sue-Ming Yang. 2012. *The Criminology of Place: Street Segments and Our Understanding of the Crime Problem*. New York: Oxford University Press.

Wilcox, Pamela, and John E. Eck. 2011. Criminology of the unpopular: Implications for policy aimed at payday lending facilities. *Criminology & Public Policy* 10:473–82.

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

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

Table S.1. Univariate Statistics for the Percentage of Americans Engaged in Activities at Different Locations by Minute of an Average Day
Table S.2. Hypothesized Statistically Significant Parameter Estimates Across Models
Table S.3. Greatest Hypothesized Parameter Estimate Across Models