How Far to Travel? A Multilevel Analysis of the Residence-to-Crime Distance

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ABSTRACT

Objectives

This study investigates whether individual- and area-level factors explain variation in the residence-to-crime distances (RC distance) for 10 offense types.

Methods

Five years of police data from Dallas, Texas, are analyzed using multilevel models (HLM/MLM).

Results

RC distances for Dallas offenders varied notably across offense types. Although several area characteristics such as residential instability and concentrated immigration were associated with the overall variance in RC distance, neither these nor the individual-level characteristics used in our models explained the offense-type variance in the RC distance.

Conclusions

Although individual- and neighborhood-level factors did not explain substantial variation in RC distance across the various offenses, neighborhood-level factors explained a significant portion of neighborhood-level variance. Other finding included a curvilinear effect of age on RC distance. The salience of these findings and their implications for future research and offender travel theory are discussed.

KEY WORDS: routine activity theory, crime pattern theory, journey to crime

1. INTRODUCTION

The environmental constraints on the mobility of offenders that affect their decisions about how far to travel from their homes to commit crime have important implications for several criminological theories (Rengert, Piquero, and Jones, 1999). For example, patterns of travel distances have implications for theories that attempt to identify the mechanisms underlying the well-known relationships between various environmental characteristics and neighborhood crime rates (e.g., Sampson, Raudenbush, and Earls, 1997). We would expect these mechanisms to differ in instances where neighborhood characteristics permit residents to commit opportunistic offenses near their homes and instances where neighborhood characteristics attract offenders to journey considerable lengths to commit crime at remote locations (Bernasco and Block, 2009). The present research aims at understanding more about offender spatial decision-making within the context of both individual- and neighborhood-level characteristics.

Some of the published work on offender travel has focused on the factors associated with variance in offender travel distances, which have customarily been called the journey to crime (Costello and Wiles, 2001; Phillips, 1980). An underlying assumption of this work is that the density and location of crime opportunities and the various ways offenders interact with their environments strongly affects offender travel behavior (Hawley, 1950; Rengert et al., 1999).

Although research about offender travel has made important advances in recent years, the literature that has resulted from this work still contains many uncertain details about how individual characteristics and geographic factors affect offender's movements. An additional shortcoming includes the fact that this literature has not simultaneously considered factors at both the neighborhood and individual levels, possibly due to uncertainties about the appropriateness of basing generalizations on factors at multiple analysis levels.

In addition to a failure to incorporate multiple analytic levels, the offender travel literature has also confronted fundamental problems about how to best conceptualize and measure the length of offender travel. For example, without uncommon information from the electronic tracking devices sometimes used for law enforcement purposes (see Rossmo, Lu, and Fang, 2012), scholars who wish to determine how far an offender travels in search of a crime opportunity are ordinarily constrained to measuring the distance from the offender's residence to the crime location (Smith, Bond, and Townsley, 2009).

Common ways to approximate these travel distances include straight-line or Euclidian distance (the shortest distance between two points), Manhattan distance (the sum of the north-south and east-west differences), and street-network distance (the shortest distance between two points using existing streets and sidewalks). Recent research, however, shows that all methods usually *underestimate* an offender's actual travel distance for several reasons including the fact that searches for offending opportunity often involve circling potential target locations, backtracking, and engaging in other forms of more complex travel behavior (Rossmo, Davies, and Patrick, 2004). Occasionally, however, the distance between residence and crime may overestimate the distance traveled when offenders begin journeys from the home of a friend or relative (Costello and Wiles, 2001).

While there may be substantial theoretical and practical relevance in the study of complete offender journey patterns, several researchers have shown that the simple residence-to-crime (RC) distance can still be useful for police investigative purposes (Rossmo et al., 2004). For this reason, RC-distance probability functions are an integral part of geographic profiling, a criminal investigative methodology used to prioritize suspects (Groff and McEwen, 2005; Rossmo, 2000).

The RC distance may also be useful to gauge whether crime prevention strategies focused in offenders' neighborhoods will simply displace offenses to remote locations. The literature on social disorganization and community efficacy, for example, suggests that efforts to reduce residential instability and otherwise increase social cohesion among neighbors may increase community efficacy in regulating its members and preventing crime (Sampson et al., 1997). Efforts to increase efficacy are more likely to succeed in crime reduction goals on a global scale if offenders do not simply go elsewhere to offend.

Following these arguments, a primary emphasis in the present work is an examination of the area-level factors associated with the distances between crime locations and the offender's residence for 25,154 offenses committed in Dallas, Texas, during the five-year period from 1998 through 2002. Unlike prior research that has labeled this distance the "journey to crime," we follow the precedent of Rossmo and colleagues (2004) by using the term "residence-to-crime" distance. This term emphasizes the importance of knowing more about the factors associated with offender travel regardless of how conceptualized, while also recognizing that the RC distance is typically dissimilar in rather substantial ways from the length of an offender's entire journey. Our work extends the existing literature on offender travel by combining techniques from geographic information systems (GIS) and hierarchical-linear/multi-level modeling (HLM/MLM) methods to simultaneously model the effects of important individual- and neighborhood-level factors. The present work also has implications for theoretical perspectives other than those addressing offender travel patterns. One concrete illustration is research about the fear of crime, which notes an often-misplaced fear of strangers and outsiders in situations where a neighborhood's residents are themselves most responsible for the local crime.

2. LITERATURE OVERVIEW

Although scholars in the early 1800s recognized that crime rates varied across spatial units (Weisburd, Bruinsma, and Bernasco, 2008), the roots of the literature on how geographic characteristics affect crime and offender travel is more directly attributable to urban sociologists at the University of Chicago during the early to mid-1900s. Led by Robert Park, these early criminologists found that crime and juvenile delinquency were strongly linked to social disorganization and poverty (e.g., Park, Burgess, and McKenzie, 1925[1967]; Thrasher, 1927; Wirth, 1928). While Park recognized the importance of offender mobility issues by describing the “mobility triangle” (Park et al., 1925[1967]), Shaw investigated how offense rates decreased with distance from Chicago’s central business district and why most crimes occurred in Chicago’s “transition zone” (1929). Around the same time, Ernest Burgess (1925) and Andrew Lind (1930) examined whether juveniles committed delinquency in their own or in remote neighborhoods. Much of their work suggested that juveniles preferred to travel short distances into neighborhoods other than their own when engaging in delinquent acts so they could gain the anonymity that was possible in more socially disorganized areas.

Work by subsequent authors soon noted that the geographic distribution of offenders’ residences and the relatively short distances offenders traveled from their homes explained a substantial portion of Chicago’s spatial crime patterns and similar patterns observed in other cities (Lind, 1930; White, 1932). Work by more contemporary scholars soon noted that average RC distances in most areas were under two miles, with most research finding crime locations within one mile of the offender’s residence (e.g., Costello and Wiles, 2001; Gabor and Gottheil, 1984; McIver, 1981; Phillips, 1980; Rengert et al., 1999; Rossmo, 2000; Stephenson, 1974; Turner, 1969). The work of Park and his colleagues laid the foundations for a line of inquiry that would eventually be called environmental criminology by the scholars who expanded this field many years later (Brantingham and Brantingham, 1981).

During the 80 years since Park initiated his research, various scholars have described several different, but not mutually exclusive, reasons why RC distances are short and which factors might explain the reasons why they vary across offenders, offenses, time, and place. A prominent explanation for the short distances is the "least-effort principle," which describes the proposition that people exert no more than the minimum physical energy required to engage in a desired activity (Zipf, 1949). Alternative explanations include beliefs that most offenders are indifferent about spatial exploration (Rengert and Wasilchick, 1985), that offenders prefer locations near their homes because they are very familiar with these areas (Ratcliffe, 2006), and that remote locations often do not allow offenders to "fit-in," making them more likely to attract attention from potential witnesses or police patrols.

Brantingham and Brantinghams' crime pattern theory (1984, 1981) suggests that offenders tend to search within their normal activity space. Their work elaborates upon routine activity theory, which holds that individuals commonly locate offending opportunities while engaged in non-criminal routine daily activities like those associated with employment, education, recreation, shopping, and socialization with friends (Cohen and Felson, 1979; Costello and Wiles, 2001; Rengert and Wasilchick, 2000; Wright and Decker, 1994). Cromwell and colleagues (1991), for example, found that opportunity was the predominant characteristic in over 75 percent of burglaries.

The tenets of both routine activity theory and crime pattern theory suggest that when all else is equal, areas infrequently visited by opportunistic offenders will produce fewer crime incidents than more regularly traveled areas (Cohen and Felson, 1979). Similarly, offenders who are employed, attend school, or have friends who live in remote locations, are more likely to offend further from home (Brantingham and Brantingham, 1981; Rengert and Wasilchick, 1985; Wiles and Costello, 2000).

2.1 RC DISTANCE VARIATION BY OFFENSE TYPE

Previous research shows significant variation in offender travel distances by crime type (Baldwin and Bottoms, 1976; Hesseling, 1992; Rhodes and Conly, 1981; Tita and Griffiths, 2005). This variation suggests that: (1) among offenders there is a real or perceived difference in the availability, benefit, or cost of various offenses at different distances from their homes; (2) distances vary between where offenders live and the opportunities for different crime types; and/or (3) offenders prone to commit different offenses differ in demographic characteristics, which subsequently are associated with different activity spaces. Different crime types have different spatial opportunity structures and involve different rewards, risks, and efforts. Consequently, offenders possessing certain demographic characteristics may be selectively found among offenders engaging in different offense types.

Drug offenses are a prime example. The geography of drug markets and the range of offender travel depends on neighborhood characteristics, whether the market is local or regional, and whether the offender is a buyer or a seller (Rengert, 1996; Rengert, Ratcliff, and Chakravorty, 2005). Drug purchasing offenses may require longer travel to a more limited number of open-air drug markets (Tita and Griffiths, 2005). Drug dealing, however, generally occurs closer to offenders' homes than other offenses, perhaps because of the need for offenders to remain in close proximity to primary social networks (Eck, 1992). Pettiway (1995) found characteristics associated with the purchase of crack were more important than individual characteristics in explaining crime distances.

A consistent finding about RC distance variation across offense types is that violent crimes occur closer to the offender's residence than property crimes (DeFrances and Smith, 1994; Rand, 1986; Rhodes and Conly, 1981; White, 1932). Pyle (1976), for example, found that the average distance traveled for crimes against persons was 1.9 miles, while the average for property offenses was 2.3 miles. Similarly, in a meta-analysis of journey-to-crime studies, Rossmo (2005) found robbery, theft, and burglary to involve longer distances than rape, murder, and assault.

Research has also established that higher robbery rates are associated with the density of illicit drug dealers, prostitutes, high schools, and retail businesses – characteristics that are not uniformly distributed across space (Bernasco and Block, 2009). For this reason, average robbery RC distances may be greater than RC distance for other offenses when offenders motivated to commit robberies travel further to reach such locations. Other research suggests that the RC distance for rape may be influenced by victim characteristics, environmental features that determine where offenders reside, and locations that attract potential victims (Boggs, 1965; Rossmo, 2000; Warren et al., 1998).

While most RC distances are short, offenders will travel further if they are professional criminals or want to target a specific victim or target type (e.g., Fritzon, 2001). There is also a positive relationship between distance traveled and the money to be obtained or the value of property stolen (Morselli and Royer, 2008; Snook, 2004). The proportion of highly motivated to more opportunistic offenders may differ across crimes, geographic locations, and offender groups differentiated by age, gender, race, or other personal characteristics (Capone and Nichols, 1976; Cohen and Felson, 1979; LeBeau, 1987; Rhodes and Conly, 1981; Rossmo, 2000).

2.2 RC DISTANCE VARIATION BY OFFENDER CHARACTERISTICS

Research on how individual differences affect RC distances has primarily focused on age, gender, and race. The literature has traditionally held that juvenile offenders are most likely to commit crimes within their home area and are less mobile than adult offenders (Baldwin and Bottoms, 1976; Gabor and Gottheil, 1984; Hill, 2003; Warren, Reboussin, and Hazelwood, 1995). The full age-distance relationship, however, is somewhat more complicated.

Chainey, Austin, and Holland (2001) analyzed RC distances in the Borough of Harrow, London, and found distances increased until the age of 18 to 19 years, then dropped until the age of 55 years. An analysis by the West Midland Police in the United Kingdom produced similar results (Clarke and Eck, 2003). This study involved a very large sample (N = 258,074) that permitted police analysts to accurately plot travel distance with age. Distances in this study increased until the early 20s, then slowly declined afterwards. Groth and McEwen (2006) found a comparable pattern for homicide trips in Washington, DC. Andresen and colleagues (2013) also observed a nonlinear (quadratic) relationship between age and distance to crime in British Columbia, Canada, though the relationship varied by crime type.

This nonlinear pattern can likely be explained by changes in opportunity with age. After the age of 16 years, most young offenders are able to obtain a driver's license. When they start working, they can afford gasoline and may eventually purchase their own car. Once finished high school, they may leave home and obtain freedom from parental supervision. As an offender ages further, however, he or she may have less free time because of work commitments and family responsibilities. Furthermore, older offenders generally have more experience and knowledge of where to find nearby targets.

Gender differences have also been identified in the literature. Researchers found male offenders traveled further than female offenders for burglary (Rengert, 1975), robbery (Nichols, 1980), to buy crack cocaine Pettiway (1995), and for a wide variety of property and violent offenses Hill (2003). Groff and McEwen (2006) observed longer journey-to-homicide distances for males than females, although the difference was not statistically significant.

Some studies, however, have found opposing results. Chainey et al. (2001) observed female offenders traveled further than male offenders for a wide variety of property and violent crimes in the Borough of Harrow, London. Female burglars had greater RC distances in Australia (McCarthy, 2007), and female residential burglars in Dallas traveled approximately twice the distance of their male counterparts (Hayslett-McCall et al., 2008). Female criminals traveled further than male criminals in the West Midlands study (Clarke and Eck, 2003). Phillips (1980) also found that female juvenile offenders in the United States traveled further than male juvenile offenders for a variety of property and conduct offenses.

The research on race differences in RC distances has been more consistent. White offenders have been found to travel further than black offenders for robbery (Nichols, 1980), burglary (Hayslett-McCall et al., 2008), serial rape (Topalin, 1992), and to buy crack cocaine (Pettiway, 1995). Phillips (1980) observed that white juvenile offenders traveled further than black juvenile offenders.

It has been proposed that some of these findings might be explained by research indicating that women, lower socioeconomic (SES) groups, and those who live in urban areas have smaller activity spaces than men, higher SES groups, and those who live in suburban areas (Chapin and Brazil, 1969; Harries, 1999). Suggestions for why (some) female offenders have shorter crime trips have also included the non-discretionary time blocks that break up their day

(Hägerstrand, 1970; Rengert, 2004), and their propensity to commit different types of crimes (e.g., shoplifting) than males (Clarke and Eck, 2003). Shorter crime trips for black offenders and other minorities have been linked with social barriers to spatial interaction (Morrill, 1965; Rose, 1969), largely due to their generally lower socioeconomic status, especially in the United States.

A few studies have examined the interaction of race/ethnicity with elements of neighborhood characteristics. Bernasco and Block (2009), for example, suggested that white non-Hispanic robbery offenders are less likely to travel to residential tracts dominated by African-American and/or Hispanic residents than to tracts dominated by other white residents. Similarly, Hayslett-McCall and colleagues (2008) found that white offenders were most likely to offend in neighborhoods with higher percentages of white residents, black offenders were most likely to offend in neighborhoods with higher percentages of black residents, and offenders whose families originated from various Central and South-American countries were more likely to offend in either white or Hispanic neighborhoods than in areas characterized by a higher percentage of black residents.

2.3 RC DISTANCE VARIATION BY GEOGRAPHIC CHARACTERISTICS AND OPPORTUNITY STRUCTURES

Locations of criminal neighborhoods, patterns of crime opportunities, and transportation links vary across the urban environment. Although a substantial body of literature has examined how these various geographic characteristics affect the distribution of attractive targets and therefore spatial crime patterns, their influence on criminal travel remains underexplored. Prior research suggests that RC distances depend upon how the city's topography interacts with the location from where the offender begins his or her travels. Most cities contain high crime rate neighborhoods, the arrangement and location of which affect RC distances (Gabor and Gottheil, 1984; Rhodes and Conly, 1981). The travel of buyers to open air drug markets is a function of the distances between market locations and their homes (Tita and Griffiths, 2005). Bichler, Schwartz, and Orosco (2010) found community-level factors, such as urban structures, land use, road networks, and transportation access were most responsible for variations in juvenile offender travel patterns in Southern California.

Factors that differentially affect particular target backcloths (the spatial opportunity structures for specific target or victim types) will differentially affect offense-specific RC distances. In other words, a geographic characteristic may influence some crimes but have little effect upon others. The locations of parking lots, for example, may affect vehicle theft rates (Tilly, 1993) but have little effect on robbery. These differences are potentially translated into RC distance variation in cases where car thieves who reside in areas with little public parking travel to places where parking lots are common.

3. THE PRESENT RESEARCH

The current research examines how RC distances in Dallas, Texas, are simultaneously influenced by crime type, offender characteristics, and neighborhood features. Dallas was chosen not only because it is the ninth largest city in the United States, with a population of approximately 1.2 million people, but also due to a unique opportunity to obtain geocoded data from the Dallas Police Department. Crime rates in Dallas are as expected for a large US city. The 2011 violent crime rate was 681 per 100,000 population and the property crime rate was 5,057 per 100,000. In comparison, the violent and property rates across the entire country were 386 and 2,908 respectively.

Our analytic models are informed by frameworks from the environmental criminology literature and supplemented by insights from social disorganization perspectives. One of the main goals of this study was to demonstrate how individual- and neighborhood-level variables might be simultaneously considered in research on offender travel by conducting an analysis of how variables at these different analytic levels influence RC distances. A second goal was to determine whether individual demographics and neighborhood characteristics could explain the variance in RC distances across offense types noted in the prior literature.

Our two main premises are: (1) factors related to the wealth (or lack thereof) of offenders and the neighborhoods in which they live affect their means and therefore their spatial behavior; and (2) opportunity differences influence RC distance variations across neighborhoods in ways suggested by routine activity theory. We hypothesize that neighborhood characteristics largely associated with socioeconomic status will affect these distances in accordance to these perspectives, but recognize that these mechanisms may produce counteracting influences. For example, while lack of wealth may constrain offender mobility, at the neighborhood level it may also reduce crime opportunities near an offender's residence, thus motivating offenders to travel further. Because the prior literature provides no guidance about the net effect of these counteracting forces, we refrain from making specific hypotheses about the direction of these neighborhood-level characteristics.

Although our dataset is relatively large, it is limited in its ability to explain variations in offender travel distances. Some of these limitations are due to the fact that the data required to perform more definitive empirical analyses are uncommon.

3.1 ECOLOGICAL FALLACY AND THE MODIFIABLE AREAL UNITS PROBLEM

A major purpose of this work is to explore how individual and community-level influences on RC distances can be examined on more than one analytic level. The offender travel research that has used multilevel modeling has only done so to examine multiple offenses per offender rather than multiple offenders per geographic area (e.g., Smith et al., 2009). More specifically, quantitative RC distance research has generally focused on information about the offense, offender, and victim, while giving little attention to how area-level characteristics affect mobility.

In some ways, the lack of information about these macro-level characteristics is surprising given the emphasis that scholars of offender travel have placed on the Chicago School sociologists and their interest in geographic-level characteristics. One reason for the small number of studies that incorporate multiple analytic levels appears to be concern among scholars about using area-level characteristics to predict individual-level behavior (e.g., Rengert and Lockwood, 2008).

Concerns about using area-level characteristics in models of individual-level behavior often reference the early work of Robinson (1950) who was partially responding to the work of the Chicago School when he proclaimed that correlations measured at the area-level cannot validly describe the behavior of individuals (Weisburd et al., 2008). Robinson's claim became known as the "ecological fallacy" in the sociological literature, while a closely related issue in the geographic literature became known as the "modifiable areal units problem" (Green and Flowerdew, 1996; Wrigley et al., 1996).

Robinson's claim has been critiqued by those who have since outlined when the use of area-level factors to infer information about individual behavior is appropriate. Hanushek and colleagues (1974) argued the issue is really one of proper model specification. These scholars noted that Robinson was writing about bivariate models at a time when multivariate regression was almost unknown due to the lack of adequate computer resources. Hanushek and colleagues noted that aggregate data increases specification problems when relevant variables are excluded from stochastic models, but argued that aggregate multivariate models are better than individual-level bivariate models or models that exclude relevant variables at different aggregation levels.

Using variables at multiple aggregation levels is now well established in the hierarchical-linear/multi-level modeling (HLM/MLM) literature (e.g., Raudenbush and Bryk, 2002), although HLM/MLM models have not seen much use in the offender travel literature. This study uses this method because HLM models permit a proper accounting for the nested structure of our data and more accurate standard error estimates.

The current work employs an HLM framework with an individual-level outcome (RC distance) where area-level predictors are *not* used to *replace* individual-level predictors (as in the case Robinson discussed), but rather to supplement them. We use census block groups for the aggregate-level because they closely correspond to the preferred characteristics for area-level choices (Rengert and Lockwood, 2008). In this case, block groups are preferred because small areas maximize between-region variance while minimizing within-region variance of model factors.

3.2 DATA

The primary data for these analyses were obtained from the GIS Analysis Section of the Dallas, Texas, Police Department. These data contain information about offenders resident in Dallas who were processed through the adult criminal justice system for crimes that occurred in this city during the five-year period from 1998 through 2002. Because family violence offenses most often occur within the offender’s home and thus involve no mobility (Tita and Griffiths, 2005), these cases were excluded from the models. Family violence offenses are identified in the original data through an indication made by the reporting police officer. For the purposes of the present analysis, we also compared the offense location with the offender’s residence and excluded cases where these two addresses matched. Our analyses excluded cases where offenses occurred in offenders' homes even if the reporting officer did not indicate that the event involved family violence because these cases do not involve an actual crime "journey." These were cases that presumably involved crimes against guests who were not family members. We excluded cases flagged as family violence even when they did not occur in offenders' residences, reasoning that a large proportion of these likely involved family members traveling together when the offense occurred (so there was no real journey) relative to the number involving separated couples living apart (where there likely was a journey).

The original data contained 56,295 arrests for the 10 offenses included in this study, of which 25,509 (45.3%) were flagged by the police as involving family violence. Another 1,718 offenses (3.1%) occurred in the offender's home. A combined total of 27,227 cases (48.4%) were excluded from our analyses for these reasons. Although the proportion of family violence arrests may appear high for these data on first glance, they are within expectations when we consider that these are *arrest* rather than *offense* data and that family violence almost always involves known offenders who are easily identified, located, and arrested. In addition, and as mentioned above, only 10 offenses, many of which are dominated by family violence cases, were included in the study. The percentage of family violence arrests relative to arrests for *all* Dallas offenses during this time period is 8.4% according to this same dataset. If data about crimes known to the police (rather than only arrests) were able to be included, the family violence percentage would be much lower.

Offenses committed by individuals outside of the Dallas area, non-Dallas residents, homeless individuals, individuals under 16 years of age, and those with unverifiable addresses were also excluded. The location of a vehicle theft was recorded as where the vehicle was stolen rather than where the vehicle was recovered.

The Dallas police data contain geocoded locations of offender residence and crime site, and include offender age, race, and gender. They contain no offender names, however, they do included encrypted offender dates of birth and geocoded offender residence locations. They do not contain information about offender employment, income, education, or similar measures of socio-economic status. Offenses were classified as the most serious crime committed during the incident. Close inspection of these data provides information permitting the identification of co-offenders. These cases can be identified when more than a single offender is listed on the same police report. We excluded cases where co-offenders lived at the same residence so as to not improperly affect our analyses (N=908 excluded).

There is some ability (although imperfect) to identify instances where the same offender is listed more than once and has committed several crimes on different dates. This can be done by determining whether individuals residing at the same location have the same date of birth. Ideally, multiple offenses committed by the same offender could be included into a third level of analysis, however, we did not attempt this due to the imperfect ability to identify these cases. We did, however, exclude all but one offense per offender (the one with the earliest date) in cases where we could reliably determine that several crimes were committed by the same offender (N=3,095 excluded).

The offense data was matched to corresponding information from land-use records from the North Central Texas Council of Governments (NCTCOG; www.nctcog.org) and data from the United States Bureau of the Census. Although the data choice was dictated primarily by a cooperative agreement with the Dallas Police Department, the choice was advantageous in two ways. First, because Dallas is a large city, it was possible to collect the necessary number of cases for sufficient statistical power. Second, both Dallas and the NCTCOG maintain records in an electronic format. This allowed RC distances to be readily calculated for various offences over a number of years, and for offender arrest data to be matched with census data containing information about variations in economy, ethnic composition, average socioeconomic status, land-use, and other key factors known to affect crime rates.

Dallas is heterogeneous across block groups in these factors, and variations exist in the degree to which each block group is zoned as industrial, commercial, residential, or undeveloped/vacant. Moreover, the socioeconomic status of Dallas communities ranges from extreme poverty to extreme wealth in a manner where pockets of exclusive neighborhoods are often surrounded by poverty-stricken areas. These contrasts provide the variation among our predictor variables that allows for better estimates of regression coefficients when we include a variety of community- and individual-level factors into a hierarchical analytic model.

The final individual-level data set contained a total of 25,154 offenses, while the block group-/community-level dataset contained 1,042 census block groups.

3.3 METHODS

HLM models are elaborations of ordinary least squares regression (OLS) that address the dependence among analytic units and associated incorrect standard errors if an OLS model is used when several units are found within the same higher-order group (Schwartz and Ackerman, 2001). Many offenders in the Dallas data, for example, live in the same block group and will therefore be affected by the same community-level factors. This aspect of these data creates a non-modeled dependence problem among offenders living in the same area, which violates OLS assumptions if OLS models were used. HLM methods account for this complex data structure and allow for the inclusion of two analytic levels in the same regression equation.

HLM models are also useful to determine whether the characteristics of geographical spatial units like neighborhoods or block groups have effects upon an outcome of interest. The present research is interested in whether criminals who reside in similar areas will travel similar distances to offend.

One of the purposes of this study was to test whether differences in RC distance across offense types could be explained by compositional differences among the offenders prone to commit the different offenses or the geographic differences in where these offenders lived. For this reason, average RC distances across offenses were examined using a model containing only dummy variable coding for the offense types in our data. Factors associated with certain offender characteristics were added to this base model to determine whether they explain why offense types have different RC distances. Subsequently, factors associated with the characteristics of the offender neighborhoods were added in a full model to see if they could explain RC distance variation across crimes. For example, even if someone intent on stealing and someone intent on murder may need to travel the same distance to locate suitable targets if all else were equal, individuals motivated to steal may tend to live in neighborhoods possessing different opportunity structures than individuals motivated to murder. In this case, RC distances may be more directly associated with the characteristics of neighborhoods than with characteristics of offenders and the types of offenses they commit.

3.4 DEPENDENT VARIABLE

The present study used street-network estimation methods to calculate the RC distance, which have an advantage over Euclidian or Manhattan distances because they more accurately reflect the actual distance an offender has to travel by considering the spatial constraints of the street network. It must be acknowledged, however, that the exact route taken by an offender is usually unknown. The models were not replicated with alternative distance measurements, as prior research has shown Euclidian and street-network measurements are strongly correlated, with the former ranging from 0.72 to 0.85 the length of the latter (Chainey et al., 2001; Groff and McEwen, 2006; Rossmo et al., 2004). Because they can easily be converted, the choice of distance measurement will not affect the regression coefficients that are of primary interest in this research.

Because RC distances are skewed, the present analyses rely upon RC distances transformed by taking their square root. This transformation provided the best approximation to normality in these particular data. Unfortunately, this transformation makes the results more difficult to interpret. As mentioned below, however, the majority of the independent variables are either dichotomies, are converted to *Z*-scores, or are scaled in a way permitting a somewhat straightforward interpretation of our results.

3.5 INDIVIDUAL-LEVEL INDEPENDENT VARIABLES

Our regression models include several demographic variables that prior research has shown to be associated with varying RC distances, including gender/female (female=1, male=0), age (in years at the date of the offense), and race/ethnicity (African-American and Hispanic dummy variables with white as the excluded comparison). Because prior research has found a non-linear relationship between age and travel distance, age-squared and age-cubed terms were included (in appropriate models), in addition to the age variable in its original metric (see Osgood et al., 1996). Because the models used data transformations and other model complexities, we subtracted 16 (the minimum age of offenders in these data) from the age of each offender so that the model's intercept corresponds to the RC distances of 16-year-old offenders. This permitted a more straightforward calculation of a curvilinear age effect in a model that also contained a transformation of the dependent variable.

3.6 COMMUNITY-LEVEL INDEPENDENT VARIABLES

Current research suggests that several community- and neighborhood-level factors are associated with crime-rate variance (e.g., Morenoff and Sampson, 1997; Sampson, Morenoff, and Earls, 1999; Sampson et al., 1997). To the extent these same factors affect the distribution of targets and victims and the frequency of situational opportunities for crime, they may also affect RC distances. For this reason, the analytic models included the following measures computed from 2000 census data: (1) *concentrated economic disadvantage*, a scaled measure that includes percent of individuals below the poverty line, percent receiving public assistance, percent unemployed, and percent of female-headed households with children; (2) *concentrated immigration*, a scaled measure combining percent of persons foreign born, percent linguistically isolated, and percent Hispanic; and (3) *residential instability*, a scaled measure combining residential mobility and percent renters.

To create the first three measures, precedents established in past literature (e.g., Morenoff and Sampson, 1997; Sampson et al., 1999; Sampson et al., 1997) were followed by first using principle components techniques to determine if the same factor structure found in prior research applied to Dallas. After confirming this to be the case, the three factors were scaled so their means were zero and their standard deviations were one by summing the *Z*-scores for each item and dividing by the number of items in each scale. Unweighted scores were used because prior research has noted similar results regardless of whether or not the items were weighted.

The next three measures were obtained directly from census data: (4) *population density*, the number of persons per square mile; (5) *percent male*, percent males in the block group; and (6) *percent 18 to 24*, percent residents between the ages of 18 and 24.

Additional neighborhood-level characteristics were calculated from NCTCOG data. Because these data are constantly updated, NCTCOG land-use information is more accurate than other sources of local land-use data, including the United States Bureau of the Census. We calculated: (7) *percent commercial*; (8) *percent industrial*; (9) *percent residential*; and (10) *percent vacant* land in each census block group by summing the total number of acres zoned for each use and dividing by the block group's total acreage. This classification of vacant is different than census measures, which use the term to define unoccupied housing units. In our case, vacant land represents undeveloped areas that have not yet been assigned a permanent zoning classification.

All community-level variables were converted to *Z*-scores (thus centering them) to aid interpretation for the main analyses in Table 3, although most were maintained in their original metric for the descriptive statistics in Table 2.

The prior literature contains no single best strategy for the choice of areal unit to use when constructing these scales. Some scholars argue census blocks best approximate a "neighborhood" or "community" (Taylor, 1997), while others prefer block groups or census tracts (Leventhal and Brooks-Gunn, 2000). This study was constricted to census block groups because they provide the smallest aggregation where all the necessary measures were available (Gatewood, 2001).

4. RESULTS

Table 1 provides descriptive statistics for the RC distances for the 25,154 offenses used in our analyses. These included 6,271 violent offenses (excluding family violence and other offenses occurring within the offenders' homes) and 18,883 property offenses. Average RC distances are listed separately for the 10 common crime classifications in these data and for the violent/property/total crime aggregations.

<< Table 1 About Here >>

While prior literature has reported typical RC distance means in the range of one to three miles (Rossmo, 2000, 2005), the Dallas data show higher means ranging from a low of 4.6 miles for murder to a high of 6.9 miles for theft. The median, however, is considered a more representative measure of central tendency (or expected values) than the mean in journey-to-crime research because distance distributions are positively skewed. The medians in these data range from 2.5 miles for residential burglary to 6.0 miles for theft.

There are a number of reasons why the RC distances in this study are longer than those found in most previous studies. The primary reason involves the exclusion of family violence offense and offenses that have occurred in the offender's residence. The choice of whether to include or exclude these cases has a major impact upon estimates of average RC distance, regardless of whether one compares means or the medians. Our arrest data started with 56,295 cases where 25,509 were flagged in the police reports as involving family violence and another 1,718 cases were reported as having occurred in the offenders' residence. In all, approximately 48.4% of the original data was excluded from these analyses for these reasons. RC distances for rape provide a good illustration of how much this matters. Before excluding family violence incidents and other incidents that occurred in the offenders' homes where the RC distance is zero, the median RC distance for rape is approximately 0.6 miles. After excluding these incidents, this median jumps drastically to around 4 miles, a greater than 650% increase.

There are three other reasons why these data indicate RC distances longer than prior studies. First, past research typically measured RC distances with a Euclidean metric; however, street-network distances, as used here, are invariably longer (from 18% to 39%, depending on the street layout). Second, criminals in Dallas may simply have longer RC distances than those found in previous studies. Given the city's large area, low density, and central role in the Dallas-Fort Worth Metroplex, Dallasites' general travel patterns and activity spaces may be larger than average. The bulk of previous journey-to-crime research in the United States has been conducted east of the Mississippi River, with only a few studies in the more sprawling western cities (Rossmo, 2000). Third, the early research in this field that occurred prior to the 1970s likely underestimates the contemporary travel distances of offenders who now have easy automobile access.

Although the RC distances reported here are longer and not directly comparable to those found in most prior research for the reasons mentioned above, the overall patterns are generally consistent with prior work in that violent crimes generally have median RC distances shorter than property crimes (4.2 miles versus 5.7 miles). Among violent offenses, rape, aggravated assault, and murder had the shortest median RC distances, while simple assault had the longest median RC distance. Residential burglary had the shortest median RC distance for property crime, which had a median distance shorter than all of the violence offenses. Theft had the longest median RC distance. An interesting point to note is that although the mean and median distances vary across offenses by up to 50% for the means (4.6 to 6.9 miles) and up to 240% for the medians (2.5to 6.0 miles), the standard deviations of the means varied across offenses by no more than 28% (4.6 to 5.9). This finding supports the position of environmental criminologists that individual crime types have distinct spatial-temporal patterns.

Table 2 displays descriptive statistics for the independent variables. The mean offender age was 29.6 years, with a range from 16 to 84 years. Females accounted for 27 percent of offenders, whites 19 percent, African Americans 55 percent, and various Hispanic groups 25 percent.

<< Table 2 About Here >>

Among the neighborhood-level variables, residential instability, concentrated disadvantage, and concentrated immigration were scaled to a mean of 0 and a standard deviation of 1 in Table 2. For the subsequent analyses reported in Table 3, the remainder of the neighborhood-level variables were scaled in the same way. Consistent with the diversity of Dallas, the population density of the city's block groups ranged from 0 to approximately 80,000 people per square mile. The block group population density mean was 6,378 residents per square mile (though the population density over the land area of the entire city was 3,518). The proportion of residents aged 18 to 24 years ranged from 0 to 83 percent with a mean of 9 percent, while the proportion of male residents ranged from 0 to 76 percent.

The percentage of land zoned for commercial, industrial and residential ranged respectively from 0 percent to approximately 71, 80, and 94 percent, with means of 6.9, 2.7, and 47.8 percent. The vacant classification, representing the percentage of undeveloped land without a permanent zoning classification in the block group, ranged from 0 to 86 percent with a mean of 14.7 percent.

The information in Table 2 reflects data from all 1,042 Dallas block groups regardless of whether a block group had residents who committed an offense. This explains why the minimum for variables like population density and percent male are zero. However, unoccupied block groups were not included in the regression analyses presented in subsequent tables.

Table 3 presents the main analyses. The first model provides results from our base model containing offense dummy coding. Recall that the analyses use the square root of the RC distances to approximate a normally distributed outcome variable. Residential burglary was used as the excluded reference category because it had the shortest mean and median RC distances. The offense coefficients in the base model therefore represent the degree to which the square-root-transformed RC distance of each offense is longer than the transformed RC distance of residential burglary net of the unmodeled block group characteristics that differentially affect the RC distances of offenders residing in different areas.

To aid interpretation, we included an additional column in each model labeled "Expected Distance." In the base model, this column represents the expected value of the RC distance for the corresponding offense on each row. It is calculated as the squared sum of the intercept and the offense's regression coefficient. For example, the expected distance for theft is $6.06 = (1.826 + 0.635)^2$. Note that while a linear regression equation using variables in their original metric produces an estimate of the conditional *mean* of the outcome given a particular value of the predictor, when the dependent variable is transformed toward normality, the equation produces an estimate closer to the conditional *median* for that offense. This is so because the square root transformation produces a more normal distribution of a positively skewed outcome where the mean and median are closer to one another. This procedure is not unlike quantile regression, which cannot yet be calculated in multi-level models (Tian and Chen, 2006).

For this reason, numbers in the "Expected Distance" column of Table 3 can be seen to be quite close to the Table 1 medians. If the outcome was left untransformed, the equivalent model would have more closely matched the means in this table. The mean, however, is generally considered a poor indication of central tendency in a skewed distribution.

One advantage to this model over the descriptive figures in Table 1 is the addition of statistical tests that determine whether the predicted distances for each offense differ in a statistically significant way from the expected distance for residential burglary, the excluded reference offense. The results indicate that with the exception of murder, aggravated assault, and rape, all other offenses have significantly longer expected RC distances ($p < 0.05$). Another advantage to this model is the ability to compare it with the second and third models to determine whether the addition of individual- and neighborhood-level variables will explain RC distance variations across offense types.

<< Table 3 About Here >>

The second model in Table 3 adds individual-level offender characteristics (age, ethnicity, and gender) to the base model. The rationale for adding individual-level factors before block group-level controls was to determine whether differences in these characteristics help explain variation in RC distance across offense type. Compositional differences are likely explanations for this variation to the extent that the more elaborate model's offense coefficients move closer to zero relative to those in the base model.

In this second model, the three age polynomial terms were based upon the lowest age in the data – 16 years. In other words, 16 was subtracted from each offender's age at the time of the event. This permits the model's intercept to represent the expected distance for residential burglary for 16-year olds who are coded zero on the remainder of the predictor variables.

Because males and white offenders were coded "0," while female, black, and Hispanic offenders were coded "1" in their respective dummy variables, these codings mean that the square of the model's intercept as shown in the "Expected Distance" column ($1.9^2 = 3.7$) represents the expected distance traveled by 16-year-old, white, male, residential burglary offenders.

Although minor differences in the offense dummy variable coefficients appeared between the first and second models, they were small and insubstantial. Many increased rather than decreased. This pattern indicates that the reasons underlying the different RC distances among offenses in the base model is not simply a result of decisions by persons of different ages, genders, or ethnicities to become involved in different types of crime.

All three age coefficients are statistically significant, indicating a non-linear age effect on RC distances. Because interpreting and visualizing the meaning of the three coefficients is difficult, a graphical representation of the curvilinear relationship between age and RC distances is shown in Figure 1. This figure represents the expected effect of age on RC distances for white, male, residential burglary offenders who reside in block groups characterized by averages on the block group-level variables in the final model.

Figure 1 indicates that net of other factors, the RC distance lengthens during the teenage years and peaks at age 26 before subsequently becoming shorter. This graph is very similar in shape to those found in the British Columbia and West Midlands studies, though the Dallas RC distances are longer (Andresen et al., 2013; Clarke and Eck, 2003) for the reasons mentioned earlier. The initial increase in RC distance across age is likely explained by greater vehicle access and more autonomy from the constraints of school and parental control. Mobility decreases after the 26-year-old peak are likely the result of a reduction in the opportunity for extensive spatial exploration caused by employment, marriage, and/or parenthood.

<< Figure 1 About Here >>

We might speculate that a portion of the age-RC distance pattern is related to a more general pattern that scholars describe as the “age-crime-curve” (e.g., Hirschi and Gottfredson, 1983). In other words, a portion of the overall age-crime relationship might be explained by a difference in the ability to find crime opportunities at different ages (see Osgood et al., 1996, for a similar argument related to age-related changes in unstructured socializing with peers).

All other individual-level variables in this model are statistically significant. Males and minorities travel shorter distances than females and non-minority groups. Females travel 0.32 miles further than males (4.02 - 3.70), while whites travel 0.57 miles further than African Americans (3.70 - 3.13) and 0.85 miles further than Hispanic groups (3.70 - 2.85).

The third model of Table 3 presents the complete HLM model with both individual- and block group-level controls. Again, in order to assist in the interpretation of the model’s intercept and the other coefficients, each of the block group-/community-level variables were converted to *Z*-scores for this analysis. Similarly to model two, this strategy causes the intercept to represent the expected distance traveled by a 16-year-old white, male, residential burglar who lives in an area characterized by average scores (*Z*-score of zero) on each of the block-group variables. When a group-level coefficient is added to the intercept’s coefficient, the square of their sum represents the expected distance predicted by a one standard deviation change in the variable. For example, a one-standard deviation increase in residential instability produces an expected RC distance of 3.09 miles for 16-year-old, white, male, residential burglars, who are at the mean of the other neighborhood-level variables. As in the prior models, this is shown in the “Expected Distance” column.

Many of the block group-level variables are statistically significant, with residential instability showing the largest effect. Here, a one-standard deviation increase in the residential instability scale predicts a decrease in expected RC distance from 3.75 to 3.09 when all of the other predictors are zero. The magnitude of this decrease is more than all of the dichotomous individual-level predictors with the exception of Hispanic ethnicity. Concentrated immigration has less effect that produces an expected RC distance of 3.46 when increased by one standard deviation. Population density also decreases RC distances to an expected value of 3.51 when increased by one standard deviation. Concentrated disadvantage has a negative, but not significant, effect.

The percentage of population aged 18 to 24 years increases the expected RC distance. A one-standard deviation increase in 18- to 24-year olds (7 percent) increases the distance to 3.93 from 3.75 miles. The percentage of males is not statistically significant.

Among the land-use variables, only percent commercial and percent vacant have statistically significant effects. An increase of one-standard deviation in percent commercial (10.4 percent) is associated with a 0.22 mile decrease (from 3.75 to 3.53), while a one-standard deviation increase in percent vacant/undeveloped (14.7 percent) results in a 0.62-mile increase (from 4.37 to 3.75).

The intraclass correlation coefficient (ICC) in these models represents the proportion of variance between block groups relative to the total variance. The variance components at the bottom of Table 3 indicate that the unconditional ICC in the base model is 0.160 (0.189 / (0.189 + 0.992)) – in other words, 16.0% of the variance is between block groups when no individual- or neighborhood-level predictors are included in the model. The ICC for the final model is 0.079 (0.084 / (0.084 + 0.975)), indicating that 7.9 % of the variance is between block groups after the predictors have been added. The overall pattern reveals that neighborhood-level variables explain a substantial portion of the overall variance in RC distances, while individual-level variables explain relatively little.

5. DISCUSSION

This research was motivated by an interest in examining offender mobility and its variation across the characteristics of both offenders and the neighborhoods in which they reside. We hypothesized that neighborhood-level variables generally associated with socioeconomic status affect RC distances for reasons similar to those proposed by social disorganization and routine activity theories, which can describe why crime rates differ across neighborhoods. Due to data limitations and the current state of theoretical development in this area, however, we did not hypothesize the specific direction of these neighborhood effects. For these reasons, we consider our analyses largely exploratory.

The findings support the idea that characteristics of offender neighborhoods are important influences on RC distances. Residential instability, for example, was found to be a stronger predictor of RC distance than most individual-level characteristics. Concentrated immigration and population density reflect greater offending opportunities and prior research has noted demographic similarities between offenders and their victims. Areas inhabited by individuals in the most crime-prone demographic categories therefore have more crime opportunities, which should result in shorter crime journeys.

If offenders living in disadvantaged areas generally have to travel further to find desirable property to steal, instability, disadvantage, immigration, and population composition would be expected to influence property and violent crime in different ways. Our findings of lower RC distances in areas of commercial land use and higher RC distances around vacant/undeveloped land provide some support for this hypothesis. Offenders who target businesses for robbery, burglary, and theft, and those who victimize patrons of commercial establishments, should find more crime opportunities as the percentage of commercial property increases and the percentage of vacant land decreases. For this reason, offenders residing in areas characterized by fewer commercial locations are likely to travel further.

Although income and socioeconomic status more generally are believed to be important forces driving many of these results, the Dallas data do not have the information necessary to more thoroughly investigate this assumption. However, almost all of the block group-level variables associated with lower economic resources are related to shorter RC distances.

Similar statements can be made about individual-level offender characteristics. Minority groups, who more typically have fewer financial resources than majority groups, traveled shorter distances than white offenders. However, males, who generally have greater financial resources, traveled shorter distances than females.

The exact mechanism by which income influences RC distances is speculative, but may be related to vehicle access as well as other factors discussed earlier. Again, these data do not contain the information necessary to further investigate this possibility.

The non-linear relationship between RC distance and offender age was particularly interesting. Increasing RC distances during the teenage years is consistent with decreasing parental control, as well as greater income and vehicle accessibility. Decreasing RC distances after the mid-20s is consistent with a reduction in available time due to increasing employment and family obligations. The Dallas age-distance results are similar to those found in other studies based on large datasets from Canada, England, and the United States (Andresen et al., 2013; Chainey, Austin, and Holland, 2001; Clarke and Eck, 2003; Groth and McEwen, 2006).

Our approach of simultaneously examining both individual- and community-level variables on the journey to crime is paralleled by recent research using discrete choice models to concurrently examine the characteristics of where criminals reside, where they offend, and where they do not (Bernasco and Nieuwbeerta, 2005). Borrowed from spatial econometrics, these models allow the combined influence of area-level characteristics and offender residential proximity on spatial crime patterns to be estimated (Summers, 2012). This approach involves the consideration of all potential location alternatives from which an offender can choose, and treats distance as an independent variable representing the probability of offender travel (Bernasco, 2007). By examining both where criminals offend and where they do not, researchers can determine the physical and socio-demographic differences between those areas, providing insight into offender spatial decision-making. Discrete choice research has shown burglars are influenced by opportunity and environmental context (Townsley et al., 2014), thieves favor accessible areas close to home and low in social cohesion (Johnson and Summers, 2014), and robbery locations are influenced by offender characteristics, crime distance, and target area characteristics such as collective efficacy, racial segregation, and the presence of illegal markets (Bernasco and Block, 2009).

5.1 FUTURE RESEARCH

Multilevel and discrete choice models permit joint theory testing and the evaluation of the simultaneous influences of different variable types on offender mobility. Analyses of large police databases permit a more detailed understanding of the specific influences of those variables. Innovative studies using DNA profiling have helped fill in some of the gaps in our knowledge, allowing for the comparison of the spatial patterns of arrested and non-arrested offenders (Lammers, 2014), and the measurement of inter-regional criminal travel (Wiles and Costello, 2000).

New approaches and modern technology have also allowed researchers to better understand the full nature of the journey to crime, movement which appears to be a much more complex phenomenon than traditionally recognized. Offenders often engage in extensive searching behavior, movement between competing target possibilities, and multiple trips over time to the offense site. Real-time location data are available from parolee electronic monitoring programs with global positioning system (GPS) capabilities, allowing for the accurate mapping of recidivist movement patterns before, during, and after the crime (Rossmo et al., 2012). Cellular telephone analysis and location information obtained from smart phones seized from offenders by police provide coarse- and fine-grained perspectives on criminal travel (Schmitz et al., 2014; see González et al., 2008).

The very concept of the journey to crime has been expanded by research on the multiple-site nature of certain offense types and the study of the hunting behavior of predatory criminals (Beauregard et al., 2007; Beauregard and Rossmo, 2007; Deslauriers-Varin and Beauregard, 2010; Rossmo, 2000; Rossmo et al., 2004). Offender travel can involve extensive search behaviors and target selection processes. Some crimes include more than one location, requiring movement between these sites (e.g., from the victim encounter location to the murder scene, from the murder scene to the body disposal site, etc.). Determining the distances between crime sites is of equal interest to researchers as measuring the offender residence-to-crime distance.

5.2 LIMITATIONS

Police arrest data only contain information on identified criminals. How well such data represent the complete offender population is a matter of debate. Inexperienced, careless, risky, and prolific offenders will be overrepresented in the data, as will those who commit crimes with higher clearance rates. Experienced, careful, cautious, and occasional offenders will be underrepresented in the data, as will those who commit crimes with lower clearance rates. These limitations pose certain problems for research purposes, and all offender travel research based upon police data will be biased to some degree. But with the exception of some white-collar criminals (whose crimes do not involve a traditional "journey" in any event), it is unlikely even experienced and cautious offenders avoid arrest altogether. Moreover, recent research using DNA profiling has not found significant differences between the spatial crime patterns of arrested and non-arrested offenders, indicating police data are unlikely to be significantly biased (Lammers, 2014).

We included different crime types in a single analytic model to determine whether differences in RC distances across offense types might be explained by compositional differences among offenders prone to commit different offenses. However, some aspects of the journey-to-crime literature suggest that individual- and community-level characteristics may differentially affect offense types. While crime-specific analyses require complex model structures, this is an approach that could provide a more detailed understanding of causal relationships and should be explored in future research.

While HLM models account for clustering of offenders in block groups, they treat spatial proximity in a binary fashion, assuming individuals who live in the same block group share context, while those living in different block groups, regardless of proximity, do not. It is possible, however, that geographic proximity may be more important for relationships than simple block group membership (Tobler, 1970). In other words, depending on how close an offender lives to the edge of a block group, he or she might be influenced by the characteristics of the adjacent neighborhood (Goodchild, 1987; Odland, 1988). In a related way, the discrete choice approach suggests that only by considering interactions between the characteristics of offenders' neighborhoods and those of all alternative offending locations can offender travel decisions be fully modeled (Bernasco and Block, 2009).

Finally, certain cases were excluded from the analyses: (1) those with unverifiable addresses, largely due to errors in the original police data; (2) family violence arrests, as such cases typically did not involve a journey to crime, and (3) multiple offenses committed by the same offender. The exclusion of the last two groups of cases affected our results by the elimination of zero RC distances and serial offender bias.

6. CONCLUSION

The journey to crime is a critical concept for theory, practice, and policy. It is integral to crime pattern theory and generates the necessary "convergence in space and time" of offenders and targets in routine activity theory (Brantingham and Brantingham, 1984; Cohen and Felson, 1979). Journey-to-crime probability distributions allow detectives to focus investigative resources and prioritize suspects through geographic profiling (Rossmo, 2000). Offender travel needs to be considered in crime prevention evaluations in order to fully measure spatial displacement (Bowers et al., 2011), while policies of sex offender residency restriction must appreciate how offenders hunt for their victims in order to be effective (Ouimet and Proulx, 1994). For these and other reasons, research that produces a better understanding of the influences and dynamics of criminal movement is important.

Previous research on modeling the journey to crime did not simultaneously examine individual- and community-level variables; for this reason, our study adds to the offender travel literature by demonstrating how influences at both levels can be explored within the same analysis. Ten crime types were contrasted in order to explore whether offender compositional differences across offense type explained variations in RC distances. While no notable differences were detected, a number of significant individual- and block group-level predictors on RC distance were found, the most noteworthy being age, minority-group status, and neighborhood residential instability. These results suggest that matters related to socio-economic status are important topics that future research on the journey to crime and offender mobility should address.

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Table I. Residence-to-Crime Distance Comparisons by Crime Type+

Crime Type	N	Minimum++	Maximum	Median	Mean	Std. Dev.
All Crime	25,154	0	29.4	5.3	6.3	5.1
Violent Crime	6,271	0	29.4	4.2	5.3	4.9
Murder	115	0	19.4	3.8	4.6	4.6
Rape	132	0	23.8	3.9	5.2	5.3
Robbery	2,243	0	28.5	4.6	5.6	4.8
Aggravated Assault	2,028	0	25.7	3.2	4.7	4.8
Simple Assault	1,753	0	29.4	4.9	5.8	5.2
Property Crime	18,883	0	29.2	5.7	6.6	5.1
Business Burglary	606	0	22.9	4.4	5.7	5.0
Residential Burglary	944	0	27.7	2.5	4.7	5.1
Theft	12,771	0	26.8	6.0	6.9	5.9
Vehicle Theft	3,900	0	26.2	5.8	6.5	4.9
Vandalism	662	0	29.1	3.6	5.2	5.0

+ Distances in miles.

++ Although crimes that occurred in the offenders' homes were excluded, rounding error of offenses near the offenders' homes produces a zero in this column.

Table II. Descriptive Statistics

Variables	Minimum	Maximum	Mean	Std. Dev.
Block Group-Level Variables (N = 1,042)				
Residential Instability	-1.65	1.97	0.00	1.00
Concentrated Disadvantage	-1.11	5.84	0.00	1.00
Concentrated Immigration	-0.94	3.73	0.00	1.00
Population Density	0.00	80,115.70	6,378.34	6,892.38
Percent 18-24 Years	0.00	83.04	9.32	6.83
Percent Male	0.00	75.82	45.72	14.74
Percent Commercial	0.00	71.04	6.94	10.40
Percent Industrial	0.00	79.84	2.67	9.45
Percent Residential	0.00	93.82	47.84	25.13
Percent Vacant	0.00	86.16	6.89	14.67
Individual-Level Variables (N = 30,779)				
Age	16.33	84.89	29.56	10.18
Female			0.27	
African American			0.55	
Hispanic			0.25	
White			0.19	

Table III. Crime Type, Individual-, and Block Group-Level Predictors of Residence-to-Crime Distance+

Variables	Models++++					
	Base		Individual		Block Group	
Crime	b++	Expected Distance+++	b++	Expected Distance+++	b++	Expected Distance+++
Intercept (Res. Burglary)	1.826 (.04)*	3.34	1.923 (.04)*	3.70	1.937 (.04)*	3.75
Murder	0.025 (.10)	3.43	0.033 (.10)	3.82	0.016 (.10)	3.82
Aggravated Assault	0.029 (.04)	3.44	0.034 (.04)	3.83	0.036 (.04)	3.89
Rape	0.091 (.09)	3.68	0.119 (.09)	4.17	0.107 (.10)	4.18
Vandalism	0.204 (.05)*	4.12	0.193 (.05)*	4.48	0.190 (.05)*	4.52
Simple Assault	0.300 (.04)*	4.52	0.284 (.04)*	4.87	0.286 (.04)*	4.94
Business Burglary	0.299 (.05)*	4.52	0.307 (.05)*	4.97	0.302 (.05)*	5.01
Robbery	0.349 (.04)*	4.73	0.346 (.04)*	5.14	0.344 (.04)*	5.20
Vehicle Theft	0.534 (.04)*	5.57	0.526 (.04)*	5.99	0.525 (.04)*	6.06
Theft	0.635 (.04)*	6.06	0.615 (.03)*	6.44	0.613 (.03)*	6.51
Individual Level						
Age +++++			0.018 (.00)*		0.019 (.00)*	
Age Squared			-0.001 (.00)*		-0.001 (.00)*	
Age Cubed			0.000 (.00)*		0.001 (.00)*	
Female			0.082 (.02)*	4.02	0.083 (.01)*	4.08
Black			-0.154 (.02)*	3.13	-0.157 (.02)*	3.17
Hispanic			-0.235 (.02)*	2.85	-0.212 (.02)*	2.98
Block-Group Level						
Residential Instability					-0.180 (.02)*	3.09
Conc. Disadvantage					-0.021 (.02)	3.67
Conc. Immigration					-0.077 (.02)*	3.46
Population Density					-0.065 (.02)*	3.51
Percent 18-24 Years					0.045 (.02)*	3.93
Percent Male					0.025 (.02)	3.85
Percent Commercial					-0.057 (.02)*	3.53
Percent Industrial					-0.009 (.01)	3.72
Percent Residential					-0.006 (.02)	3.73
Percent Vacant					0.153 (.02)*	4.37
Variance Components						
U_0	.189		.183		.084	
r	.992		.975		.975	

+ The dependent variable is transformed to the square-root of the RC distance. The standard errors are in parentheses.

++ Because the RC distance was transformed using the square-root function, the offense coefficients represent the difference between the square-root of the distance for residential burglary (the excluded reference) and the square-root of the distance for that offense.

+++ This column represents the expected value of the RC distance for 16-year olds when all other predictors are zero.

++++ The block-group level variables have all been converted to Z scores.

+++++ 16 years has been subtracted from the offender's age so that the intercept represents the expected value of the RC distance for residential burglary for 16-year-old white male offenders, who live in areas that are average on all of the block-group characteristics. This permits the age polynomials to be used to calculate Figure 1.

* $p < 0.05$.

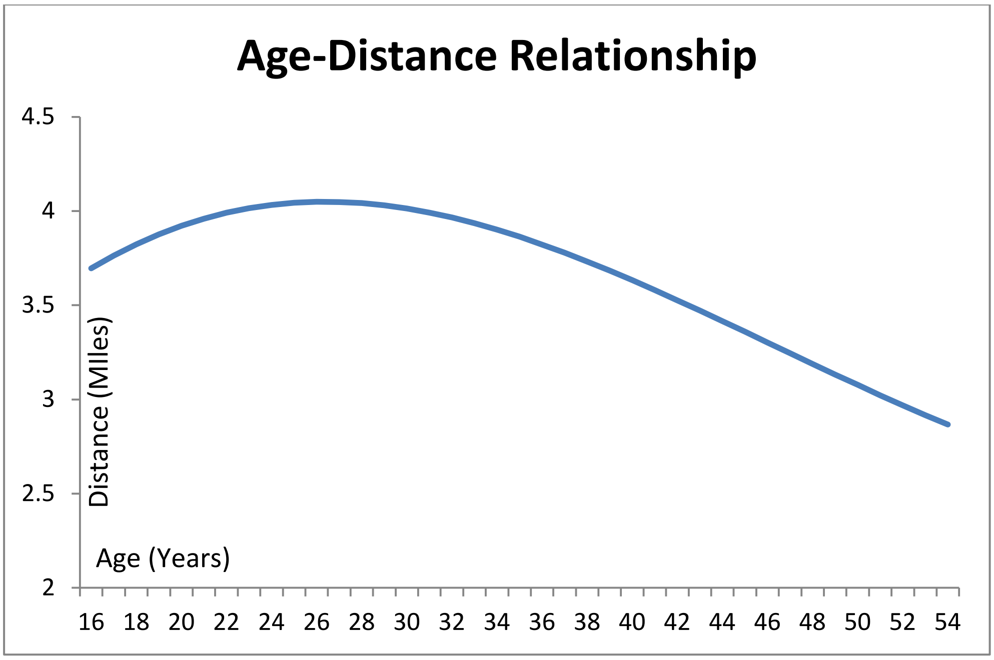

Figure 1. RC Distance by Offender Age.