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Risk factor and high-risk place variations across different robbery targets in Denver, Colorado

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Abstract:

Purpose

Risk Terrain Modeling (RTM) has been effectively used to spatially diagnose risk for crimes such as robbery, aggravated assault, and gun violence. An important contribution is to consider how risk differs across individual crimes and different target types. This study tests four different robbery target types in unique models to examine the potential for variation across significant risk factors and high-risk locations.

Methods

Using the online diagnostic software RTMDx, individual robbery models were run for four robbery target types in Denver, Colorado: commercial (businesses), carjacking (driver/vehicle), residential (home/dwelling), and street (pedestrians). A conjunctive analysis of case configurations was also conducted to determine the potential for spatial differences in high-risk places across target types.

Results

The results indicate that there is variation across risk factors, and observable differences in risk factor spatial influence, operationalization and relative risk values in each target model. Convenience stores were the only risk factor significantly associated with every target type and the conjunctive analysis matrix found that very few places were high-risk for all four robbery types.

Conclusions

The findings suggest different target types should be analyzed individually and interventions should focus on different high-risk locations and be tailored to specific target types.

Keywords:

risk terrain modeling, crime generators and attractors, situational crime prevention, conjunctive analysis of case configurations, robbery

Citation:

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1. Introduction

Situational crime prevention (SCP) has been widely heralded in the criminological evidence-base and applied to address issues of crime at highly localized levels. A key tenet of SCP is that crime opportunities are unique. Therefore, broad crime category classifications and assumptions about the contributing factors in high crime environments need to be further parsed out for better problem understanding (Felson & Clarke, 1998). Modern interpretations and expansions of SCP suggest that potential offenders can be deterred if opportunities are diminished, when the benefits of crime outweigh the risk, and when changes in the environment successfully alters the reward structure (Clarke 1992, 1997). Putting this to practice means that if conducive crime settings can be identified and manipulated, crime and public safety problems can be adequately addressed and ultimately reduced or eliminated through individualized solutions. The current study proposes that situational crime prevention can be more readily accomplished by focusing on singular crimes and target types.

Risk Terrain Modeling (RTM) is an empirical technique that assesses the spatial dynamics of crime within a geographically defined environment (Caplan, Kennedy & Miller, 2011). It has been successfully operationalized to understand the spatial risk for a variety of crime types, including robbery (Barnum et al. 2017), carjacking (Lersch, 2017), aggravated assault (Valasik, 2018), motor vehicle theft and recovery (Piza et al., 2017), and gun violence (Drawve, Moak & Berthelot, 2016; Piza & Gilchrist, 2018). RTM models help determine the relative risk and the spatial influence of environmental, manmade, and physical features. The findings generated by RTM demonstrate how these features both individually and collectively contribute to the outcome event's likelihood of occurrence. The emphasis RTM places on focused problem understanding leads to specialized solutions and interventions tailored to

singular problems (Caplan & Kennedy, 2016; Kennedy, Caplan, & Piza, 2018). However, to best understand the problem's origin and its associated risk factors, it is imperative to also have a nuanced understanding of the outcome being evaluated.

The current study contributes to the literature on RTM and SCP through a spatial analysis of robbery in Denver, Colorado. Analyses were conducted on four varying robbery classifications based on the type of target victimized: commercial (targeting businesses), carjacking (targeting drivers and their vehicles), residential (targeting persons within homes or dwellings), and street (targeting pedestrians). Results indicate that there are variations across risk factors, and observable differences in risk factor spatial influence, operationalization, and relative risk values in each target type model. Only one risk factor, convenience stores, was significantly associated with every robbery target type and many risk factors (11) were only significant in one model. A conjunctive analysis of case configurations found that a very small proportion of micro-places in the study area were deemed high risk for multiple types of robbery, and less than 0.5% of the city was high-risk for every robbery target type. This suggests that a range of SCP interventions should be designed to address each unique type of robbery, and that interventions should focus on different places within the city.

2. Review of Relevant Literature

2.1 Understanding Robbery

The crux of this study is that robbery, like many other crimes, is generalized into a larger umbrella definition with highly specific sub-types attached secondarily. It is important to note that robbery not only involves different targets and victims, but it plays out in different fashions (e.g. the level of force used, the weapon selected). Robbery also unfolds in different settings (inside structures and outside in open-air environments), and it can occur at random or through

premeditated selection. Lastly, robbery occurrence is also highly contingent on both the macro (city) and micro (block-level) environment. Barnum et al. (2017) examined the associated risk factors for robbery across three major US cities: Newark, Chicago and Kansas City. The researchers found that the number of significant risk factors as well as the range, weight, and extent of associated relative risk values varied across cities. In addition, many of the 14 risk factors (laundromats, parking stations, variety stores, bars, schools, parks and pawn shops) identified as correlates of robbery in prior research were not significant in all three cities (Barnum et al., 2017). These findings highlight the importance of studying robbery both in micro-environments and across disaggregate typologies, as elements like the setting and target type may be crucial in identifying accurate risk factors.

Comprehending the definitional differences across crime types requires the understanding that there is potential for different crimes to occur in different settings, different crimes to occur as the result of different risk factors, and different crimes to vary in occurrence across space. Haberman (2017) examined hot spots of different crime types to determine the potential for overlap in Philadelphia, PA. Haberman found that the hot spots for 11 different crime types did not overlap very much, indicating different crimes often do occur in unique environments. However, in increasing our understanding of crime patterns and developing crime prevention interventions, it is imperative to analyze not just the difference between various crime types and their variance in space, but the disparate behaviors that encompass singular forms of crime. Andresen and Linning (2017) explored this phenomenon by examining the appropriateness of broad crime categorizations in spatial research and determined that aggregating crimes into general categories (e.g. property, violent) does not adequately reflect the situational element of opportunity and target selection different crime types entail.

Relatedly, different forms of robbery also entail their own situational constructs and opportunity frameworks. Theoretical perspectives focusing on crime opportunity have also underscored the conception that the opportunity to commit crime is an essential cause of crime (Felson & Clarke, 1998). Target selection is central to routine activities theory and its later developments which proposit that both a suitable target and a location without capable guardianship are two of the three major elements in the crime triangle (Cohen & Felson, 1979; Eck, 2003). Crime pattern theory suggests that offenders make crime templates which often involve aspects they desire in ideal victims (Brantingham & Brantingham, 1993a), and the daily movements of potential victims that intersect and run along the nodes, pathways, and activity spaces of offenders make certain targets more attractive (Brantingham & Brantingham, 1993b).

Given these theoretical insights, focusing on a target-based classification system allows for simultaneously more exhaustive and nuanced conclusions that can be situated against other types of robbery. Police data often record the type of robbery that occurred as it pertains to the charge, weapon involved, or event description, but the target type victimized may also have paramount importance when it comes to understanding the likelihood of event occurrence. Examples include commercial robbery, in which offenders forcibly take goods or proceeds from a business; carjacking, which involves the forcible hijacking of a motor vehicle; residential robbery, which is characterized by forced entry into a residential home or dwelling often referred to as a home invasion; and street robbery, in which offenders target pedestrians and other individuals in public places. The potential for unique spatial distributions of these robbery types may mean that they are each associated with different spatial risk factors.

Indeed, robberies targeting commercial settings (Hendricks et al., 1999; Herrmann et al., 2012), residences or living spaces (Heinonen & Eck, 2012), drivers and their vehicles (Lersch,

2017), and occurring against individuals on the street (Bernasco, Ruiter & Block, 2017) have each been attributed their own sets of risk factors and rationales. In this vein, the study by Lersch (2017), an RTM analysis of carjackings occurring in Detroit during the year 2015, is particularly informative to the current study. Lersch (2017) found that only six of a potential 14 risk factors were significantly associated with carjacking: vehicle service stations, convenience/grocery/liquor stores, bus stops, restaurants, drug arrests, and demolitions. The highest risk areas, marked by high co-location of the aforementioned risk factors, experienced an expected carjacking rate that was 278 times higher than other locations.

Understanding that targets for each form of robbery are acquired for different reasons has led to different event narratives for each robbery target type, and different deterrence efforts focused on eliminating crime opportunities. Commercial robbery reduction efforts have focused on increased security personnel and the use of technology, and especially at-risk businesses like convenience stores and banks have incorporated target hardening measures like bullet-proof glass and other barrier structures designed to separate the offender from the desired good (McCluskey & Cancino, 2013). Environmental factors such as an isolated home, and/or a home without any natural measures of security have been suggested to be more conducive to residential forms of robbery (Heionen & Eck, 2012). Street robbery has been linked to other illicit markets, like drug and prostitution rings, because street robbers have demonstrated a tendency to target other lawbreakers who are less likely to report the crime and more likely to possess cash (Wright & Decker, 1997). This research highlights the need to parse out robbery through unique target classifications.

2.2 Theoretical Underpinnings

With priority placed on environment as opposed to people, RTM follows the frameworks outlined by crime-and-place theories. Early works from the Chicago School were some of the first to assert that crime was unevenly distributed across space (Shaw & McKay, 1942) and that crime tends to concentrate in delineable zones (Burgess & Park, 1925). Crime pattern theory later emerged due to its ability to integrate the built environment with theories designed to understand offender motive and human involvement. Under the framework of crime pattern theory, areas are more likely to become prone to crime if they attract and/or generate opportunity. Crime generators create a space for crime through gathering large sums of people, promoting movement and transiency, and facilitating access to victims (Brantingham & Brantingham, 1995). Crime attractors are known locations that offenders are drawn to explicitly for the purpose of committing crimes as that is the reinforced behavior within the given environment (Brantingham & Brantingham, 1995). The spatial and temporal overlap of these crime environments feeds into an offender template (Brantingham & Brantingham, 1981), which is an ideal backcloth (Brantingham & Brantingham, 1993a) that fits an offenders desired opportunity and plan for crime execution (Brantingham & Brantingham, 1993b; Brantingham & Brantingham, 2008).

The opportunity to commit a crime is a key cog in the commission of crime and in the framing of many criminological theories. Original rational choice theorists such as Beccaria, Hobbes and Bentham implied that crime is engaged in only when the hedonistic calculus of the offender determines that the reward of the crime outweighs the risks. Later developments (Clarke & Cornish, 1985; Cornish & Clarke, 1986) contended that part of the calculation involves an assessment of the physical environment, meaning that both location, target, and opportunity are pertinent to offender decision-making. Routine activities theory (RAT) explains the opportunity

framework through the intersection of three components: a victim, a motivated offender, and a suitable target with the absence of capable guardianship (Cohen & Felson, 1979). The fundamental contention of RAT is that when victims and offenders intersect in appropriate settings the opportunity for crime emerges and likelihood of occurrence increases. As such, places with higher levels of crime opportunities (i.e. crime generators and attractors) are likely to report higher levels of crime than places absent these features. These developments helped inform SCP and the notion that certain places are more susceptible and favorable to crime than others.

The idea of criminal opportunity has been expanded to include exposure considerations in the form of past crime events, functions of proximity and density to risk inducing features, and the absence or presence of protective measures (Cohen, Kluegel & Land, 1981). Modern research has come to look at opportunity and risk similarly, understanding that interpreting these measures as probabilities means that the chance of the outcome is rarely, if ever, zero (Kennedy & Van Brunschot, 2009). Thus, the onus no longer rests on singularly identifying who is involved in the crime but instead where opportunity exists, where it is the greatest, why it exists there, and what can be done about it (Eck, 2002).

2.3 The Current Study

The current study uses RTM to determine if the most at-risk locations, and corresponding significant risk factors, vary when assessing robbery by target type in independent models. We build upon prior RTM research that has demonstrated unique risk factor patterning across study settings (Barnum et al., 2017). Kennedy (1983) compared urban settings to a kaleidoscope, with the individual shards of glass symbolizing individual risk factors comprising a larger place or environment, and every turn of the kaleidoscope creating new patterns, colocations, and

configurations of spatial risk factors. This process may potentially play out across other spatial extents, including more micro-settings and across different forms of robbery as this study is examining. Thus, this study hypothesizes that like the changing nature of environments and risk across different geographic boundaries, study areas and spatial extents, each robbery target type will have its own patterning of risk factors and its own set of high-risk places.

3. Method

3.1 Study Setting and Data

The current study focuses on Denver, Colorado, which encompasses a population of 700,000 people within 155 square miles.¹ Denver is the largest city in Colorado and remains one of the fastest growing cities in the United States. Additionally, the tourism industry in Denver is robust with over 30 million visitors annually. The data for this study came from several sources. The robbery data for the calendar year 2016 (N=1,146) was provided by the Denver Police Department's Data Analysis Unit and included amenable XY coordinates with a pre-referenced coordinate system. Each incident was individually recorded and classified for the study based on the sub-type of robbery that police officials listed (commercial, carjacking, residential, or street).

The outcome variable examined in this study was robberies occurring within the jurisdiction of the Denver Police Department during the calendar year 2016. Four separate models were run to correspond to each identified robbery type. The commercial classification (N=301) contained all robberies occurring at a business or commercial setting, including banks. Carjacking's (N=119) were classified as robberies committed against drivers or vehicle

¹ The square mileage for the city of Denver also includes the Denver International Airport, which sits to the northeast of the main portion of the city. The Denver Police Department handles all criminal offenses that occur at the airport, and the dataset obtained included other crimes that recorded incidents on airport grounds. No robberies occurred on airport premises in the calendar year 2016, however, the boundaries of the airport were left within the study area as the risk values for the airport cells are important in understanding robbery across the entire landscape of Denver.

occupants. Residential robberies (N=84) were coded as home invasions or robberies that involved the entrance of a dwelling as the locational target. Street robberies (N=642) were those committed against pedestrians when the individual(s) and their possessions or goods were the target of the robbery, this also included forcible purse snatchings.

The risk factors analyzed included businesses, mappable places, and other related geographically bound locations that were downloaded from the Denver open data portal² or purchased through Infogroup.³ Infogroup is a leading provider of spatial data, especially due to their rigorous maintenance of active business licenses, and has been frequently incorporated in risk terrain modeling analyses (Caplan et al., 2017; Caplan et al., 2014; Piza & Gilchrist, 2018; Piza et al., 2017) and into the larger body of spatial research in criminal justice (Piza, Caplan & Kennedy, 2014; Miller, Caplan & Ostermann, 2016). All risk factor datasets contained XY coordinates or came as shapefiles that were easily transferable into a geographic information system (GIS) for spatial analyses and the RTM process. The Risk Terrain Modeling Diagnostics Utility (RTMDx) was used for the analyses and was made available through the Rutgers Center for Public Safety.

The selection of the risk factors incorporated to contextualize micro-places was determined through prior literature noting robbery correlates, literature focusing on factors associated with violent crime outcomes, and by assessing business and feature types by their capacities as crime generators or attractors. Following the modern developmental approach of RTM research and analyses, the inclusion of a multitude of potential risk factors that could be logically connected to robbery were utilized in the model (Thomas & Drawve, 2018; Valasik,

² <https://www.denvergov.org/opendata>

³ The Infogroup risk factors included: ATMs, bars, banks, check-cashing/payday loans, liquor stores, nightclubs/lounges, and restaurants

2018). It is a strategically advantageous approach to include a high number of risk factors as the model then simultaneously serves to prevent mediation by avoiding unincluded variables, and by accounting for as many potential causally related factors as possible. The full list of risk factors in the models, their count, and their vector type can all be seen in Table 1.

Table 1: Risk Factors

Risk Factor	N	Vector
ATM	28	Point
Banks	21	Point
Bars	129	Point
Body Art	39	Point
Check Cashing/Payday Loans	17	Point
Convenience Stores	276	Point
Dollar Stores	34	Point
Foreclosures	699	Point
Hotels	89	Point
Laundromats	30	Point
Light Rail Stations	25	Point
Liquor Stores	9	Point
Medical Marijuana	35	Point
Motels	29	Point
Nightclubs/Lounges	77	Point
Parking Garages	119	Polygon
Parks	336	Polygon
Pharmacies	22	Point
Points of Interest	134	Point
Public Art Installations	327	Point
Restaurants	543	Point
Retail Marijuana	164	Point
Schools	35	Point
Shopping Centers	212	Polygon
Small Grocery	65	Point
Supercenters	8	Point
Supermarkets	43	Point

Many of the included measures could be described as crime generators, such as: city parcels classified as shopping centers like retail outlets and strip malls, supermarkets and supercenters, large parking garages, outdoor parks, city points of interest which encapsulate all landmarks and tourist attractions, and public art installations. These features encourage the gathering of large sums of people in settings potentially conducive to robbery and may create

opportunities and templates desirable to offenders. Bars and nightclubs have been identified by prior literature as known crime attractors and have been found to have a specific relationship with robbery (Bernasco & Block, 2011; Haberman & Ratcliffe, 2015). Other factors like public transit stops,⁴ foreclosures, convenience stores, restaurants, banks and ATMs have also been found to be linked to robbery and other forms of violent crime (Gaziarifoglu, 2015; Miethe & Sousa, 2010; Lersch, 2017).

Marijuana related businesses, although now legal in Denver, were included as potential attractors due to their reinforcement of behaviors previously deemed illegal and illicit. Persons frequenting these newly established businesses may further make ripe targets for robbery offenders. Also, following the opioid and prescription drug epidemic plaguing the United States pharmacies were included for the potential robbery of materials not just finances. Other businesses that are more likely to run on cash-based transactions or sell a highly desirable product may also enhance the risk of robbery (St. Jean, 2007; Wright & Decker, 1997); these include check cashing and payday loan services, laundromats, liquor stores, hotels and motels, dollar stores, and small grocery stores. Schools were also included as a risk factor considering the relationship between age and crime, as young people are more likely to be both offenders and victims than any other age cohort, and some studies suggest violent crime is more likely near schools (Bernasco & Block, 2009). Lastly, tattoo and piercing shops were included in the model based on their inclusion in prior RTM research (see Thomas & Drawve, 2018), specifically their inclusion in violent crime models (Drawve, Thomas, & Walker, 2016). They are also a high frequency cash-based business that may have an effect on robbery in Denver that has not been previously explored.

⁴ The 25 transit stops include Denver's six light rail stations, which provide service to major event centers, stadiums and the airport.

This analysis has a high number of risk factors due to the demonstrated relationship between environment and crime, thus justifying the inclusion of attractors, generators, unique business operations and other potentially risky environmental elements. Additionally, this analysis includes a high number of risk factors due to the well-researched differences in setting, likelihood, and motivation resulting from target selection across different forms of robbery. This study will help determine if unique risk factors research has associated with certain target types are actually significant with their prescribed target, and further, if variation across risk factors and high-risk places in each different robbery target type model are observable. To accomplish this, risk factors were held constant across all four models.

3.2 Risk Terrain Modeling

Following the observations that crime is not randomly distributed across time and space (Weisburd, 2015), that very few locations in a geographic area are responsible for the majority of all crime (Sherman, Gartin & Buerger, 1989), and that the locations responsible for crime can be reduced to micro-places like street segments or street blocks (Weisburd, 2008), RTM attempts to take this information and ultimately determine what locations are inherently riskier and identify the spatial factors that may explain why (Caplan, Kennedy & Miller, 2011). This approach expands upon the identification and subsequent deployment of police resources to hot spots by diagnosing the spatial risk factors that help to sustain hot spot areas (Kennedy et al., 2015; Caplan & Kennedy, 2016). Thus, RTM can help inform police practices by identifying features of the environment that police can directly account for when designing crime reduction initiatives (Kennedy, Caplan & Piza, 2018).

RTM suggests that certain places, which contain features that overlap and combine within an environment, foster a greater likelihood of crime occurrence (Kennedy, Caplan & Piza,

2011). The way that these features both individually and jointly affect outcomes and behaviors in their immediate landscape can be articulated through the factor's spatial influence, which is the understanding of how a feature can dictate its surrounding environment (Caplan & Kennedy, 2016). We used RTMDx version 1.5.0.0 for the analysis (Caplan & Kennedy, 2018). Each robbery target type model was run in succession with the same risk factors and parameters held constant, with the dependent variable tested being the only change (Commercial N = 301; Carjacking N = 119; Residential N = 84; Street N = 642). The City of Denver was broken down into 87,025 places, or equally sized grids for the analysis, with each place representing a 250 ft by 250 ft cell corresponding to half the average downtown block length in Denver (Denver by the Data: Volume 1)⁵.

RTMDx tested for spatial relationships between each of the 27 different risk factors, and their ability to individually and collectively influence the outcome variable at every place in the study area. The RTMDx software tests the influence of each risk factor on crime and their appropriate spatial operationalization – which is whether proximity to the feature or density of the features significantly manipulates the outcome. Proximity refers to being close to just one count of a singular risk factor type whereas density refers to the level of risk being higher in places that have a statistically significant clustering of a given feature. Nearest neighbor analyses nested within the RTMDx software determine which spatial operationalization is selected for each significant risk factor. The spatial influence of each feature operationalized was tested in whole block increments up to three blocks, creating three variables for each risk factor (1 Blk = 450 ft, 2 Blks = 900 ft, 3 Blks = 1,350 ft).

⁵ http://www.confluence-denver.com/features/denver_by_the_data_1_011415.aspx

Testing each of the 27 risk factors at whole block increments up to three blocks may create issues with spurious correlations due to the large number of variables created. However, the penalized regression model implemented by RTM involves an iterative process that creates the most parsimonious model through continually assessing the Bayesian Information Criteria (BIC) (Heffner, 2013; in Caplan, Kennedy & Piza, 2013). An elastic net method is employed that forms five stratified folds from the raster cells spanning the study area. For each variable, RTMDx runs a model for each fold to measure the influence of the tested risk factor on the dependent variable. Any non-zero coefficients are assigned predictive values that are then run through a bi-directional stepwise regression to determine model significance. Through an iterative process the most parsimonious model is determined. Following a null model with no risk factors, RTMDx adds each variable to the null model and re-measures the Bayesian Information Criteria (BIC) score to identify the most parsimonious combination of variables. After each iteration, the model with the lowest BIC score is selected as the new candidate model. RTMDx repeats the process, adding and removing variables one step at a time, until no variable addition/removal surpasses the previous BIC score. RTMDx repeats this process with two stepwise regression models: one Poisson and one negative binomial, selecting the best model with the lowest BIC score. Relative Risk Values (RRVs) are assigned to each risk factor included in the final model. RRVs can be interpreted as the weight of the individual risk factor, and therefore may be used for comparison across all risk factors (for more information on the statistical procedure of RTMDx, see Heffner, 2013).

3.5 Conjunctive Analysis of Case Configurations

In order to explore the potential for spatial overlap of high-risk areas across robbery types, we used the conjunctive analysis of case configurations (CACC) approach (Miethe et al.,

2008). CACC is a tool for summarizing categorical data by creating a matrix that compiles all possible combinations of categorical attributes. For each cell in the city of Denver, we created a binary variable that measured where the cell was high risk, defined as having a relative risk score greater than 2 standard deviations above the mean. Four such binary variables were generated for each robbery type included in the analysis: carjacking, commercial, residential and street. We used CACC to generate all possible configurations of high-risk places and their overlap across target types by depicting in rows if a target type achieved significance.

Unpacking the behavior settings and their unique configurations of risk factors that result in high risk places across the city can help better tailor responses and solutions. CACC and RTM have been used in collaboration before to empirically determine the places influenced by the colocation of criminogenic features (Caplan et al., 2017). This study takes a different approach by using RTM to determine which risk factors are significant and which places are high-risk due to the co-location of multiple significant risk factors. The CACC was then applied to determine behavior settings and high-risk places for different robbery target types which allowed for conclusions to be drawn regarding the potential overlap of high-risk places across different robbery target types.

4. Results

4.1 Carjacking Robbery Targets: Model Results

The findings of the carjacking model are displayed in Table 2. Four of the 27 risk factors had significant results in the model: convenience stores, foreclosures, pharmacies and restaurants. Convenience stores exerted the highest impact on robbery with an RRV of 3.94, suggesting that places within a one block proximity of a convenience store are almost four times as likely to experience a carjacking as compared to places without a convenience store or the

spatial influence of another significant risk factor. The other three risk factors all exhibited an impact on carjacking that was between 2.5-3 times greater than places without a significant risk factor.

Table 2: Carjacking Targets Significant Risk Factors

Risk Factor	Op.	S.I.	RRV
Convenience Stores	Proximity	1 Blk	3.94
Foreclosures	Proximity	3 Blks	2.97
Pharmacies	Density	3 Blks	2.83
Restaurants	Proximity	3 Blks	2.50

4.2 Residential Robbery Targets: Model Results

Table 3 displays the results of the RTM analysis focused on residential robbery targets. Only three of the 27 risk factors were found to be significantly related: motels, convenience stores, and foreclosures. Motels exhibited the strongest effect on residential robbery with an RRV of 5.36. As a function of proximity, the findings indicate that places within two blocks of a motel were over five times as likely to experience a residential robbery than places without a motel or the spatial influence of any other significant risk factor. Also, as functions of proximity, convenience stores (4.78) and foreclosures (2.85) were deemed significant in the model, with both generating significantly greater risks for residential robbery than places without a significant risk factor at the two and three block level respectively.

Table 3: Residential Robbery Targets Significant Risk Factors

Risk Factor	Op.	S.I.	RRV
Motels	Proximity	2 Blks	5.36
Convenience Stores	Proximity	2 Blks	4.78
Foreclosures	Proximity	3 Blks	2.86

4.3 Street Robbery Targets: Model Results

The results of the street robbery model indicate there are 12 risk factors that are significantly associated with street robbery in Denver (see Table 4). However, only three of the

risk factors have RRV values greater than three times the risk of other places in Denver without a significant risk factor. Denver's light rail stations were significant as a function of proximity and exhibited an effect on street robbery that was more than four times as strong as any other significant risk factor. Places within one block of a light rail station were 14.60 times more likely to experience a street robbery compared to other places in Denver without a significant risk factor. Places with a motel (density: 1 blk – 3.01) or restaurant (proximity: 1 blk – 3.01) were also over three times as likely to experience a street robbery compared to other places in Denver absent significant risk factors.

Table 4: Street Robbery Significant Risk Factors

Risk Factor	Op.	S.I.	RRV
Light Rail Stations	Proximity	1 Blk	14.60
Motels	Density	1 Blk	3.01
Restaurants	Proximity	3 Blks	3.01
Supermarkets	Proximity	1 Blk	2.58
Convenience Stores	Density	3 Blks	2.44
Check Cashing/Payday Loans	Density	2 Blks	2.17
Hotels	Proximity	3 Blks	2.02
Nightclub/Lounge	Proximity	2 Blks	1.93
Medical Marijuana	Density	3 Blks	1.67
Bars	Density	3 Blks	1.67
Foreclosures	Proximity	3 Blks	1.67
Public Art Installations	Proximity	2 Blks	1.66

4.4 Commercial Robbery Targets: Model Results

The findings of the commercial robbery model are displayed in Table 5. Although it may stem from circular reasoning that some form of a business establishment must be present for a commercially-based robbery to occur, and despite many of the risk factors being businesses, this model is able to potentially discern what business establishments are at the greatest risk of being targeted for commercial robbery or create settings conducive to commercial robbery. Thus, it is still beneficial to uncover what risk factors and businesses are most connected to this specific

robbery target type, and which places are generating the most potential commercial robbery opportunities. Additionally, the focus of this study is on data classification and methodology. This manuscript serves to challenge the notion that risk factors are identical across all forms of robbery. Determining if crimes should be disaggregated by type and target is the central contribution of this study opposed to revealing the narratives and event contexts that make risk factors significant in a given model. The results in Table 5 below show that being within one block of a cluster of convenience stores makes a place over 8.72 times more likely to experience commercial robbery than other places in the city absent a significant risk factor. All seven other significant risk factors also expressed RRVs more than two times as likely to experience commercial robbery compared to the least risky places in the city.

Table 5: Commercial Robbery Targets Significant Risk Factors

Risk Factor	Op.	S.I.	RRV
Convenience Stores	Density	1 Blk	8.72
Supermarkets	Proximity	2 Blks	4.65
Dollar Stores	Proximity	1 Blk	2.82
Restaurants	Proximity	1 Blk	2.58
Pharmacies	Proximity	3 Blks	2.40
Retail Marijuana	Density	3 Blks	2.15
Schools	Proximity	3 Blks	2.12
Small Grocery	Proximity	2 Blks	2.07

4.5 Risk Variations

There are some notable distinctions across the models that lend support to the central contention argued in this paper, that unique robbery targets and settings need to be analyzed differently. Findings demonstrate that only one factor is conducive to all robbery types – convenience stores. However, examining the street robbery model exclusively because it is a highly feared form of violent crime (Wright & Decker, 1997), and because it occurs the most frequently in Denver, would diminish the importance of this finding because convenience stores

are the fifth highest RRV value in the street robbery model and may be overlooked in lieu of seemingly more pertinent factors. The street robbery model suggests light rail stations are salient in understanding situational factors of street robbery (RRV = 14.60), but this risk factor is not significant in any other model. Not only do factors appear and disappear in each of the different models, their spatial influence, operationalization, and RRVs often changed dramatically as well. Additionally, 17 of 27 risk factors operationalized were significant in at least one model. This underscores the importance of considering each robbery target type and setting in its own unique light. Figure 1 provides a visual aid for seeing the discrepancies across each individual RTM.

Figure 1: Risk Factors Grouped by Model Frequency

In the same way we can determine what risk factor(s) appear in every target type model, it is also vital to understand why some risk factors only appear in a single model. The main

contention of SCP argues that crime plays out in unique environments and under unique circumstances. Thus, blanket interventions and generalized programming not targeted at specifically identified risk factors will likely have less impact than those focused on specific risk factors for specific robbery targets. This study indicates that robbery target types have their own sets of risk factors, and many risk factors are specific to singular forms of robbery. To reduce or eliminate robbery related to a certain target type, the individual risk factors that may only influence one target type must be determined. In risk-based policing (Kennedy, Caplan & Piza, 2018), the final step of the analytical process is the identification of micro-places with disproportionate co-locations of spatial risk factors. Such places are appropriate target areas for placed-based interventions given their heightened risk for crime. This identification process is assisted by the calculation of each grid cell's relative risk score (RRS) in RTMDx. In calculating each cell's RRS, RTMDx uses map algebra to sum the RRV of each significant risk factor with a spatial influence that overlaps the defined boundaries of a given grid cell.

In following the approach of prior RTM research, we designated all cells with RRS values greater than 2 standard deviations above the mean as high-risk. We repeated this process for each of the four models to identify high-risk places for each robbery type. For commercial robbery the mean RRS was 2.80 and the standard deviation was 12.83. RTMDx selected 1,092 places (1.76% of the study area) as high-risk ($RRS > 28.46$). For carjacking the mean RRS was 3.35 and the standard deviation was 5.98. There were 2,415 places (2.78% of the study area) selected as high-risk for carjacking ($RRS > 15.31$). For residential robbery the mean RRS was 2.85 with a standard deviation of 4.90. Because of the relatively low mean and standard deviation, likely a result of the low number of residential robberies (84), the RTM output identified 6,256 places (7.19% of the study area) that were high-risk ($RRS > 12.65$). For street

robbery the mean RRS was 4.53 with a standard deviation of 13.64. There were 1,750 places (2.10% of the study area) identified as high-risk for street robbery ($RRS > 31.81$).

In considering the application of place-based interventions, an important question pertains to the potential overlap of high-risk areas for different targets. As our findings suggest, prevention programs targeting different types of robbery likely need to incorporate diverse approaches since each robbery type is influenced by a different set of risk factors. Indeed, this need for tailored responses is in line with prior research on SCP (Clarke, 1997; Felson & Clarke, 1998) and evidence-based policing more generally (Lum, Koper & Telep, 2011). However, police may be able to implement numerous strategies at the same place and within the same intervention if high-risk areas for the disparate robbery targets significantly overlap. Conversely, if high risk areas are dispersed, then each intervention will need to be deployed within distinct areas in order to target high-risk cells for the appropriate robbery target. Figure 2 displays the high-risk cells for each robbery target type. While high risk areas for the four maps seem to overlap in certain parts of Denver (namely the central portion of the Downtown area) many places in the city seem to have unique robbery problems. This suggests that interventions focusing on disparate robbery targets may require focus on different places in the city.

Figure 2: High Risk Places in Denver Across Robbery Classification

We utilized the CACC approach to also identify the places in the study area with RRVs greater than two standard deviations above the mean (i.e. high-risk cells) for each robbery type (see Table 6). Each row in the table represents a unique case configuration (CC) of high-risk designations, which prior research has referred to as behavior settings (Caplan et al., 2017; Hart & Miethe, 2015). The individual cells in the matrix contain a binary measure denoting whether the unique behavior setting observed was identified as high-risk for the given robbery type. We observed 16 unique behavior settings. The most dominant configuration (CC14) included cells deemed not high-risk for any of the robbery target types. This behavior setting comprised the vast majority of cells (91.02%). The second most common behavior setting (CC13) comprised cells marked as high-risk for residential robbery. While this behavior setting accounted for only

4.42% of the study area, it represents nearly half (49.27%; N=3,850) of high-risk cells. The remainder of the 3,964 high-risk cells were spread across 13 behavior settings. Only 258 of these cells were high-risk for all 4 robbery types (CC2), accounting for 3.30% of high-risk cells and only 0.30% of the entire study area. Furthermore, only three behavior settings, cumulatively accounting for nearly 18% (1,387 of 3,964) of all high-risk cells, related to a single robbery type. The remainder of behavior settings were related to cells deemed as high-risk for 11 different combinations of robbery types.

In selecting areas for intervention, police can also base deployment decisions on observed crime counts within particular case configurations. This can help deployment decisions as scarce resources can be utilized in the micro-places that are most likely to benefit. It is also important to note that because certain CC's were observed more frequently than others, they were also more likely to experience robbery. To account for this, we calculated the relative frequency of crime (RFC) as a proportion of robbery incidents per the number of times that a CC was observed. Following the approach of Caplan et al. (2011), we interpret RFC values in response to the average of all CC's, which was 13.18 in our sample.

As can be seen in Table 6, our most common behavior setting (CC14) had an RFC of 0.66, accounting for less than half of all robbery incidents (45.64%) despite containing 91.02% of all cells. Moreover, about 9% of the overall land area in Denver accounts for about 55% of the robbery incidents. This observation concurs with prior research demonstrating that crime is highly concentrated at places (Lee, Eck & Martinez, 2017). In looking at RFC values for other behavior settings, we begin to see the benefits of focusing on areas at high-risk for multiple robbery types. Seven of the 16 behavior settings (CC1-CC7) had an above average RFC. Five of these included cells that were high-risk for multiple robbery types. This suggests that, while they

do not represent the bulk of the study area, behavior settings at risk of multiple robbery types may provide crime prevention benefits to police as target areas. They also may allow for increased efficiency because police can incorporate multiple crime prevention interventions (directed at different types of robberies and potentially different risk factors) within single areas.

Table 6: Conjunctive Analysis of Case Configurations Matrix

CC	Street	Commercial	Carjacking	Residential	N	% City	% High Risk Cells	Crime Count	% Crime	RFC
1	yes	yes	yes	no	26	0.03	0.03	12	1.05	46.15
2	yes	yes	yes	yes	258	0.30	0.30	68	5.93	26.36
3	yes	yes	no	no	72	0.08	0.08	18	1.57	25.00
4	yes	no	yes	yes	267	0.31	0.31	54	4.71	20.22
5	yes	no	no	no	621	0.71	0.71	95	8.29	15.30
6	no	yes	yes	no	55	0.06	0.06	8	0.70	14.55
7	no	yes	no	no	278	0.32	0.32	37	3.23	13.31
8	no	yes	yes	yes	312	0.36	0.36	39	3.40	12.50
9	yes	no	no	yes	487	0.56	0.56	58	5.06	11.91
10	no	yes	no	yes	90	0.10	0.10	8	0.70	8.89
11	no	no	yes	yes	991	1.14	1.14	72	6.28	7.27
12	no	no	yes	no	488	0.56	0.56	27	2.36	5.53
13	no	no	no	yes	3850	4.42	4.43	127	11.08	3.30
14	no	no	no	no	79211	91.02	na	523	45.64	0.66
15	yes	no	yes	no	18	0.02	0.02	0	0.00	0.00
16	yes	yes	no	yes	1	0.00	0.00	0	0.00	0.00

NOTE: CC=Case Configuration. RFC=Relative Frequency of Crime. A total of 87,025 raster cells fall within the study area of Denver. CCs presented in bold text demonstrated RFC values greater than the mean of 13.18.

5. Discussion and Conclusion

Findings from the current study advance the body of knowledge in several ways. First, this study expands the evidence base by connecting place-based correlates of crime to different robbery target types. Many (17 of 27) risk factors used in the study were significant in at least one robbery target type model. This finding offers support for the Kaleidoscope analogy illustrated previously (Kennedy, 1983). Different robbery target types and different areas of the city have differing likelihoods of experiencing each form of target-based robbery and have robbery risks determined by different risk factors. This finding suggests that just like the turning of a kaleidoscope, each new environment across the city is characterized by new levels of risk and new configurations of risky features. This corroborates the notion that the elements of the immediate environment that research have deemed important in crime and place literature are also largely relevant to understanding different forms of robbery.

Second, this study opens new avenues of RTM research by demonstrating the ability of RTM to parse out crimes by target type to determine unique risk factors in each setting, and by utilizing an approach that runs multiple models with slight changes in the dependent variable as opposed to a singular comprehensive model. Andresen & Linning (2017) suggested that generalized crime categories like “violent” and “property” do not reflect the unique nuances and situational elements of the different crimes that fit under those terms. Similarly, this study contends that determining the risk factors and high-risk places for crimes like robbery needs to be predicated on more specific sub-types, as running comprehensive analyses may overlook situational elements of specific crime types. Variation was seen in multiple forms across the target models. The same sets of risk factors were not significant in each model, operationalization, and spatial influence changed, and RRV’s did not hold constant across

targets. This suggests that each robbery type bears its own spatial dynamics that create an environment most conducive to the occurrence of a particular form of robbery. This also leads to the conclusion that each sub-form of robbery is not just unique in rationales, pretenses, and execution, but also in the environment in which it is most likely to occur.

These implications affect a variety of stakeholders with different vested interests. Researchers should examine crime by parsing out crime by sub-type, considering differences in targets or related distinctions like location of occurrence or weapon used, comparing and contrasting risk factors across unique models, and assessing spatial differences in high-risk places across models. Police and law enforcement are also tasked to better classify data by including target types and other sub-information pertinent to umbrella crime definitions like “robbery.” As the FBI continues their push to require local law enforcement to report according to the protocols of the National Incident Based Reporting System (NIBRS), the need to align recorded data with key descriptives and relevant information for analyses becomes greater (Strom & Smith, 2017). The future of data collection can include improved classifications and advanced analytical capacities that lead law enforcement and researchers to stronger conclusions.

This study includes important considerations for the future of spatial research methodologies and place-based interventions. The identification of the risk factor most central to each form of robbery, observing risk factors only significant for one target type, and the detected reoccurrence of risk factors in more than one model, all provide an opportunity to implement more specific and accurate solutions to robbery. The results suggest a shift in law enforcement application of RTM. Police should focus on specific crime problems instead of relying on results from more comprehensive models when attempting to tailor solutions to micro places. Researchers and academics can also build upon this study by exploring other multi-faceted crime

types such as varying forms of assault to determine if there are unique spatial and risk factor considerations across different forms.

Prior research has explicitly used RTM to determine risk factors, and CACC to determine spatial overlap of risk factors. However, this study adds to the possibilities of crossover applications of these methods by determining high-risk places using RTM and the spatial overlap of these places using CACC. The findings of the CACC rendered further support for the framework of SCP, suggesting that there are spatial differences in high-risk locations when considering robbery by the target victimized. In alignment with prior research, the findings of the CACC determined that robbery is concentrated in very small pockets across Denver, with 91.02% of cells having no risk for any form of robbery. This finding indicates that each target type had its own set of places only high-risk for that target type and other high-risk places that overlapped with at least one other target type. Furthermore, only 258 of 87,025 cells (less than half a percent of the total study area and only 3.30% of high-risk cells) were at high-risk for all robbery forms. The finding that a small percentage of cells were high risk for all robbery types provides police with an actionable, more manageable number of optimal locations where they can potentially impact all forms of robbery. However, intervention efforts should not be limited to wide swaths of areas seemingly affected by robbery, but instead should be built in respect to specific forms of crimes with specific risk factors at specific high-risk places. Less than half a percent of Denver was high-risk across all target types. Police can focus on these locations and have a greater impact on varying forms of robbery, but the risk factors are not constant across each type and may make it difficult to successfully implement a comprehensive intervention. Police efforts may be better utilized in focusing on high-risk places for singular target types

where the risk factors can be more causally connected to the outcome, and therefore, more effectively intervened upon.

Despite their implications for research and practice, these findings should be interpreted cautiously due to several limitations that exist across the entirety of crime and place research. The models incorporated 27 risk factors so that each model would be conducted in the same way save the change in the dependent variable. The high number of independent variables generated through this process may have introduced issues of spurious correlation. The RTMDx utility has a built-in penalized regression method designed to counter issues of spuriousness, though (See Heffner Chapter 8 in Caplan, Kennedy & Piza, 2013). By pushing variable coefficients toward zero, and by selecting the optimal amount of penalization for each coefficient, the initially larger set of variables is reduced to a much smaller set list by only including the non-zero coefficients in the model. Nonetheless, we acknowledge the issues that may arise due to the large number of independent variables incorporated.

Some potentially significant environmental predictors such as pawnshops, demographic features, and other community level structural variables are missing from the analyses. All the models, but especially the commercial robbery model, are unfortunately limited to available risk factor datasets, and the crime data obtained did not contain a business identifier to parse out the exact establishment a commercial robbery occurred at. Many of the risk factors identified by empirical research and environmental criminology maintain the importance of commercial establishments and businesses on crime. However, in light of this limitation, prior research has found that place-based features can remain significant even when community level variables are injected into the analysis (Drawve, Thomas & Walker, 2018). Although, future research should

look to also include neighborhood level constructs and risk factors beyond commercial establishments to strengthen findings.

This study was only conducted in one city. Denver is one of the 20 largest cities in the United States, but as a midwestern urban setting, it varies greatly in land area and population density compared to other major American cities. Future work should test for variations across robbery types in multiple cities to determine if the phenomenon of setting specific risk factors emerges in different city contexts.

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