A VARIED SPATIAL AND TEMPORAL EXAMINATION OF VACATION HOME RENTALS AND CRIME

by

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DEDICATION

Dedicated to the belief that an unreasonable work ethic is enough.

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LIST OF ABBREVIATIONS

Abbreviation	Description
VHR	Vacation home rentals
CBG	Census block groups
RAT	Routine activity theory
ORCA	Organization of space, regulation of conduct, control of access, and acquisition of resources
STR	Short term rental
PIN	Place-in-neighborhood
SCP	Situational crime prevention
MAUP	Modifiable areal unit problem
$AR_{(p)}$	Autoregressive series of order x
$I_{(d)}$	Integrated series of order x
$MA_{(q)}$	Moving Average series of order x
ADF	Augmented Dickey-Fuller test
KPSS	Kwiatkowski–Phillips–Schmidt–Shin test
$ARIMA_{(p,d,q)}$	Autoregressive Integrated Moving Average
$SARIMA_{(p,d,q,x)}$	Seasonal ARIMA

ABSTRACT

This dissertation examines vacation home rental (VHR) properties in Austin, Texas in relation to residential burglary, substance crimes, and disturbances. The dissertation takes a three-study approach, examining VHRs in Austin with three different units of analysis. The first study uses 2018 data and neighborhoods, operationalized as census block groups (CBGs). CBGs are mutually exclusive regions with non-overlapping boundaries and varied spatial dimensions. The second study assesses result robustness by using CBGs with 2016 data, and by also using egohoods, a method of operationalizing neighborhoods with overlapping boundaries and fixed spatial dimensions. The third study uses months as the unit of analysis with a time-series design to examine VHRs and crime in the city. For the two initial studies, count regression models, social disorganization variables, spatial lag, and geographic analyses are used. For the third study, seasonal autoregressive integrated moving average (ARIMA) models are used to analyze monthly data from November 2014 to December 2019 (n=61). Vacation home rental data are reported and contextualized in different kinds of neighborhoods in the city, and in different manners per study. The most prominent finding is that listing type appears to matter. Room-only rentals were significantly and positively associated with crime, in every model that included them. However, the associations for entire-structure rentals varied by crime type, year, and neighborhood operationalization. Some of the implications are that greater scrutiny should be used to understand renter differences of these properties, as well as the property owners that rent rooms versus entire structures.

I. INTRODUCTION

The research question guiding this work is whether and to what extent there is an association between vacation home rentals (VHRs) and crime. VHRs are sometimes referred to as "transient vacation rentals" (Jordan & Moore, 2018), "home sharing lodging" (Yang et al., 2019), or as "home shares" (Binns & Kempf, 2021). For this dissertation, VHRs are measured with Airbnb data, and they refer to a loosely regulated rental situation in which (typically) private citizens rent their homes to strangers.[1] Instead of assessing all types of crime, this dissertation concentrates on residential burglary, substance crimes, and disturbances. These crimes are used instead of others for a combination of theoretical reasons that come from environmental criminology (Andresen, 2014; Brantingham, Brantingham, & Andresen, 2017) and due to other research on rental properties (Maldonado-Guzmán, 2020; Rephann, 2009; Roth, 2021b; 2021c).

There are several potential explanations for how VHRs cause crime (Binns & Kempf, 2021, p.15). For example, these explanations could include criminogenic tenants and inadequate property management (Eck & Wartell, 1998), neighbors of VHRs exploiting the VHR properties while they are unoccupied (Roth, 2021a) between tenants, or other kinds of neighborhood dynamics (Browning et al., 2017). For example, Binns and Kempf (2021) provide dozens of examples of criminogenic hosts, guests, and circumstances surrounding VHR usage at the individual level. These instances include several kinds of offenses, such as drug use, harassment, and prostitution. However, they also include fraudulent activities, liability concerns, and ways that hosts and guests may

[1] "Subletting," the practice of renting a property under one's own name and further renting that property to others, is not addressed in this dissertation. However, Hati et al. (2021) address this issue in their systematic review of Airbnb research.

better prepare themselves when considering VHR properties.

This dissertation considers the neighborhood dynamics more than the individuals associated with VHRs. Specifically, when properties in a neighborhood experience weekly resident turnover and bouts of inoccupancy, as is the case with VHR properties, neighbors are less likely to have meaningful interactions in their everyday activities. These everyday interactions are important for establishing a mutual understanding of inappropriate activities, influencing the likelihood of intervention when inappropriate activities occur, and building a sense of neighborhood community. However, crime theory and criminogenic property research further addressed in Chapter II as they relate to VHRs.

This dissertation will attempt to answer the question in three ways, and the ways are discussed as numbered studies. The first study is of vacation home rentals in Austin, Texas in 2018 and uses census block groups (CBGs). The second study is a robustness check, analyzing data again in CBGs, but for 2016, then analyzing data with egohoods - a different operationalization of neighborhoods (Hipp & Boessen, 2013). The third study uses time-series data to analyze vacation home rentals in Austin, Texas from November 2014 to December 2019. Like other criminological research, VHR and crime associations are not conducive to experimental designs, and because of this, there is instead a reliance on the consolidated evidence from multiple less than perfectly designed studies (Campbell & Stanley, 1963).[2] The three studies presented in this dissertation are an attempt to provide a patchwork of support for understanding the association between

[2] While this refers to an apt reason to have multiple studies and approaches in this dissertation, due to the newness of the topic, a mass of news articles is often used to consider VHRs and crime (Binns & Kempf, 2021, pp.15-23).

vacation home rentals and crime. This patchwork of designs considers data from different years (2018, 2016, 2014 to 2019), data in a spatial format (CBGs), in a temporal format (seasonal autoregressive integrated moving average [ARIMA] models), and with a different operationalization of neighborhoods (egohoods).

While these three studies are connected by their intent to analyze crime and VHR properties, they are also connected through the inclusion of considerations about observational dependencies. For the two studies in this dissertation using geographic units of analysis, this takes the form of spatial econometrics (Anselin, 2003; 2010; Anselin & Bera, 1998). The third study using time-series analysis takes these dependencies into account by identifying and correcting for the presence of seasonal processes, autoregressive processes, integrated processes, or moving average processes (Enders, 2015; McDowall et al., 2019). Spatial econometrics refers to a sub-discipline that accounts for spatial autocorrelation and heterogeneity issues (Anselin, 2003), and includes spatial lag variables and spatial error models (for examples of these used in criminology, see Kubrin & Weitzer, 2003; Hipp & Boessen, 2013; Boessen & Hipp, 2015; Roth, 2021b). *Chapter II* provides several explanations for why crime incidents may be co-influenced by external factors, and why incidents may influence each other, both spatially (Brantingham & Brantingham, 1995; Weisburd et al., 2016) and temporally (Baumer & Wright, 1996; Curiel, 2021; Linning, Andresen & Brantingham, 2017). These considerations persist throughout the dissertation.

There are several hypotheses to be addressed in this dissertation, all pertaining to the overarching research question. The first study asserts the following three hypotheses regarding CBGs:

H1: Vacation home rentals will be positively associated with residential burglary in CBGs.

H2: Vacation home rentals will be positively associated with substance crimes in CBGs.

H3. Vacation home rentals will be positively associated with disturbances in CBGs.

The second study asserts the same three hypotheses, but with egohoods (Hipp & Boessen, 2013). Additionally, hypothesis 4 concerns system instability and robustness (Farrington et al., 2019; Pridemore et al., 2018). Confidence in the results would be provided if *Chapter IV* (study two) mirrors the results from *Chapter III* (study one) but uses different years and with an additional spatial unit of analysis.

H4: Model results for CBG analyses will be the same in study two, compared to study one, using data from 2016 instead of 2018.

H5: Vacation home rentals will be positively associated with residential burglary in egohoods.

H6: Vacation home rentals will be positively associated with substance crimes in egohoods.

H7. Vacation home rentals will be positively associated with disturbances in egohoods.

The third study assesses the last three hypotheses using a time-series design. This study examines vacation home rentals and crime associations over time.

H8: Vacation home rentals will be positively associated with residential burglary over time.

H9: Vacation home rentals will be positively associated with substance crimes over time.

H10. Vacation home rentals will be positively associated with disturbances over time.

The first way that the research question will be answered is by analyzing vacation home rentals in Austin, Texas in 2018. *Chapters II* and *III* expand upon Reinhard (2021) in several ways. First, a more thorough literature review is provided regarding VHR and crime research, relevant criminological theory, and neighborhood operationalization as it pertains to the decision to use CBGs instead of census tracts, street segments, or some other unit of analysis. Second, data are used to compare reported rental properties in the city to VHR data. Correlations are provided comparing these data, which represents an additional contribution because the extant literature suggests that VHR properties are often not reported to authorities (Katz, 2015; Valentin, 2021). This itself is often a crime. Moreover, it is unknown how accurate crime studies are that only rely on reported rental properties. For example, it could be that owners of rental properties who report to the city represent the least criminogenic property owners. If this were the case, research may find that rental properties are less criminogenic than they really are. Third, this study addresses criticisms of criminology research with a detailed examination of neighborhoods, census data, and data aggregation concerns. This is relevant because intrinsic to this dissertation is the notion that VHRs influence the neighborhoods in which they belong. However, decades of criminology research and the recent delineation of crime science have repeatedly and justifiably asserted several issues with doing this

(Lawton, 2018; Weisburd et al., 2016).

Fourth, data are used to explore neighborhood socioeconomic status, vacation home rental locations, and average costs of rental properties in various parts of Austin, Texas. The underlying idea is that VHRs may influence neighborhood crime and neighborhood disadvantage influences crime. Examples include whether affluent neighborhoods primarily have comparably priced rental properties, and whether VHRs represent a greater proportion of properties in affluent neighborhoods than in disadvantaged ones. Fifth, descriptive data are provided regarding the state of vacation home rental properties in Austin, Texas in 2018. Information is provided, such as the proportion of property owners who own multiple properties, other ownership characteristics, and the average length of time that VHR properties are listed.

The second way that the research question will be answered is by presenting a check of the robustness of the first study, using Austin crime data from 2016 and by using CBGs and egohoods as the spatial units of analysis. This second study is important for numerous reasons. The first is that by using a different year than study one, additional confidence is gained in the results (Farrington et al., 2019) regarding VHRs and crime. It is possible that as VHRs are increasingly popularized among prospective rental property owners, the owners take additional precautions to prevent renting to criminal tenants, or more care is taken to closely monitor their own properties (Rephann, 2009). While using many of the same methods as study one in terms of variable construction, the second study also then uses a different unit of analysis, egohoods (Hipp & Boessen, 2013; Kim & Hipp, 2020). There is evidence to suggest that egocentric neighborhood construction may more closely approximate neighborhood dynamics and activity patterns (Pinchak et al., 2021). Egohoods are named by their use of beginning at city blocks (Hipp & Boessen, 2013) or individual street segments (Kim & Hipp 2020) and expanding outward with the use of Euclidian or Manhattan buffers of uniform distance (e.g., one-quarter mile, or one-half mile). It is asserted that constructing neighborhoods in this manner, in which each neighborhood is influenced by surroundings in all directions, it removes the arbitrariness of census boundaries, which implicitly suggest uniqueness in areas that may not be unique.

The third way that the research question will be answered is by using time series methods to analyze vacation home rentals and crime in Austin, Texas from November 2014 to December 2019. A time-series design is employed to better understand the temporal order of properties and crime in the city. While a debate currently exists within the criminal justice literature on the value of cross sectional versus longitudinal data (e.g., Cullen et al., 2019), using a temporal method provides further confidence in the previously obtained cross-sectional results. With the cross-sectional results, there is a greater risk of attributing crime to properties before properties were used in the manner of interest: as rental properties.[3]

Because of the shifting of units of analysis between the studies, the *Background* also discusses topics, such as "micro-spatial areas" (Andresen & Linning, 2012), spatial aggregation, geographic units of analysis (Boessen & Hipp, 2015; Lawton, 2018; Weisburd et al., 2009), and spatial considerations for facility influence on crime (e.g.,

[3] Numerous directions for future research are provided in Chapter VI. For example, it is possible that future research finds that VHR properties are associated with greater crime when they are unoccupied with renters, or that non-rental properties are more crime prone, and become less crime prone once they are rented-these topics concern occupancy issues and property management issues (see Eck & Madensen, 2018; Roth, 2019).

Cozens et al., 2019; Ratcliffe, 2011). The inclusion of both geographic units of analysis (for studies one and two), and temporal units of analysis (for study 3) presents a unique, though not uncommon (e.g., see Boessen, 2014; Hewitt, 2017; Spaulding, 2020) interest in a combination of spatial and temporal approaches in dissertations. While efforts are made to address the transition from spatial to temporal units, it may also be interpreted as triangulation (Palys & Atchison, 2021).

It is worth noting some of the many contributions this dissertation provides. First, while VHR use is believed to be increasing (Kathan et al., 2016; Sheppard & Udell, 2016), there is very little research about VHRs and crime (e.g., Roth, 2021b; 2021c; Xu et al., 2019). Xu et al. (2019) provide information about VHRs in counties in Florida in 2016, while Roth (2021b) increases geographic precision by considering VHRs in census tracts in 2017. However, decades of criminology research have found that aggregation level is an important consideration (Lawton, 2018; Weisburd et al., 2009).[4] This dissertation adds to the literature by examining the associations between VHRs and crime using a smaller spatial unit of analysis (i.e., census block groups), by checking the first study's results against a second study using the same city, and by using five years of VHR and crime data, which has not been previously done. No study, to my knowledge, has previously documented the VHR and crime relationship this comprehensively (Table 2.1), and this dissertation provides recommendations and future directions in *Chapter VI*.

Lastly, this dissertation is presented in a three-study approach (e.g., similar to Hewitt, 2017; Smith, 2020). The approach is aptly named because it focuses on the

[4] Many discussions exist about the appropriateness of certain geographic units, for example, see Weisburd et al. (2016, pp.8-11), Boessen and Hipp (2015), Rengert and Lockwood (2009), and Brantingham et al. (2009). This discussion persists throughout the dissertation and more information is provided in *Chapters III-VI.*

presentation of three interrelated studies as a means of demonstrating a unique contribution to a discipline similar to what is expected with the traditional dissertation style. However, this approach presents unique strengths and weaknesses compared to the traditional approach. One potential weakness is that when the three studies are poorly framed within overarching research objectives, quality suffers throughout. It is not enough to produce and bind together three unrelated studies. One potential strength of this approach is that sections of the dissertation are in a more usable form for academic publication and knowledge dissemination. For this dissertation, *Chapter III* corresponds to Study 1, *Chapter IV* to Study 2, and *Chapter V* to Study 3.

II. BACKGROUND[5]

Crime events are not uniformly distributed, a fact known for over a century.

- Eck and Weisburd, 1995, p.12

Vacation home rental properties, or other kinds of rental properties, likely influence and are influenced by their surroundings. This warrants broad considerations of neighborhoods, rental properties, and relevant crime theory. There are many kinds of research that consider crime in residential neighborhoods. For example, neighborhood effects research (Sampson, 2011; Sampson et al., 2002), research on gated communities (Wang et al., 2021), land use that affects residential places (Wuschke & Kinney, 2018), neighborhood crime from insiders versus outsiders (Boivin & Felson, 2018; Bowers & Johnson, 2015; Brantingham & Brantingham, 1993, p.304-306), and so forth. Neighborhoods may affect residences, for instance, neighborhood street structure affecting burglary risk of homes (Davies & Johnson, 2015); however, burgled homes may also increase the likelihood of future burglary of other homes nearby in what is known as *near-repeat victimization* (Groff & Taniguchi, 2019; Townsley, Homel, & Chaseling, 2003).[6] Top-down and bottom-up approaches to considering whether neighborhoods are influencing addresses, or crime is emanating from addresses to affect entire neighborhoods, are both viable approaches for understanding crime at places (Linning & Eck, 2021, pp. 2-4).[7] Concerns about neighborhood boundaries and some of the

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[5] Parts of *Chapters II - III* appear in the publication:
Reinhard, D. (2021). The influence of vacation home rentals on neighborhood crime and disorder. *American Journal of Criminal Justice*, 1-17. https://doi.org/10.1007/s12103-021-09635-8

[6] Each of these research areas has substantial scholarship and overlap. For example, near-repeat burglary has been studied for residential homes, but also for apartments (Glasner et al., 2018).

[7] See also “place in neighborhood” (PIN) research, for example, Tillyer et al. (2021).

neighborhood effects research are presented in *Chapter III* and *Chapter IV*. This chapter addresses temporary accommodations and crime within neighborhoods, such as apartments, hotels, and vacation home rentals, before turning toward theoretical frameworks and the application of these frameworks to understand VHRs and crime.

Rental Properties and Crime: Non-VHRs

Research on VHRs and crime has only existed within the last five years.[8] However, research has existed on other kinds of short-term rentals (Rephann, 2009), apartments (Deryol & Payne, 2020; Gilchrist, Deryol, Payne, & Wilcox, 2019; Payne, 2010; Townsley et al., 2014), hotels (Ho, Zhao & Dooley, 2017; Smith et al., 2000), motels (Bichler et al., 2013; LeBeau, 2012; Schmerler, 2005), and single-room occupancies (SROs; Krupa et al., 2019). It may be useful to understand other kinds of rental properties and accommodations because it is unclear whether VHRs are characteristically similar to residences, commercial properties, or both. For example, a substantial amount of research has considered occupancy, foreclosure, and vacancy of structures (Boessen & Chamberlain, 2017; Cui & Walsh, 2015; Roth, 2019), but a VHR property is presumably occupied uniquely compared to traditional residential properties in several ways.[9] VHRs may contribute to the presence of neighborhood outsiders (Boivin & Felson, 2018; Brantingham & Brantingham, 1993) and ambient populations in

[8] The earliest quantitative study is in 2019. Other recent publications have noted the lack of quantitative research in this area (e.g., Binns & Kempf, 2021, p.23). The recent empirical literature typically relies entirely on news sources for information about crime and VHRs.

[9] VHR properties may be occupied concurrently by strangers for shared-room or multi-individual room properties, independently of the structure owner or while the structure owner stays at the property. Occupants are likely foreign to the neighborhoods in which the properties are located. Occupancy of VHR properties may also be seasonal.

neighborhoods (Boivin, 2018), though no research has applied these concepts to rental properties yet.

Rental properties and rental property guests are typically found to be positively associated with crime; hotels, motels, and SROs are commonly described as risky facilities, crime generators, or crime attractors (Bichler et al., 2013; Eck, Clarke, & Guerette, 2007; Krupa et al., 2019; LeBeau, 2012; Tillyer et al., 2021). For example, Wuschke and Kinney (2018) found that commercial properties, including hotels and motels, exhibited greater crime rates than apartments, multi-family dwellings, and residences. Smith et al. (2000) found that blocks with hotels and motels were positively associated with street robbery. Guests may be more commonly victimized than local residents also (Ho, Zhao, & Dooley, 2017; Yang & Hua, 2020). Tillyer et al. (2021) found that hotels and motels were positively and significantly associated with drug, property, and violent crime. A review of 109 relevant crime and tourism studies similarly concluded that crime is an issue in the tourism industry, including among hotels, motels, and areas around those establishments (Hua et al., 2020). However, not all of these properties are equally likely to be criminogenic-crime may concentrate among some of them more than others.

The *law of crime concentration* (Weisburd, 2015; Weisburd et al., 2016) is typically understood as crime disproportionately occurring among or affecting a small sample of total units, such as street segments, addresses, or parcels.[10] This crime concentration has also been described as an *80-20 rule*, in which 20% of places account for 80% of crime, or as a *J-curve* (Blair, Wilcox, & Eck, 2017; Lee et al., 2017). This has

[10] This *law* had been established through numerous prior studies of crime (particularly at micro-places), and has since been supported in several contexts (e.g., Hardyns et al., 2019).

been found among properties and land uses. An analysis of land parcels with apartments, mobile homes, commercial housing, or residential land use codes found that 1.1% of residential properties contained over 20% of calls-for-service (CFS) in a city (Payne, Gallagher, Eck, Frank, 2016). This is similar to results for motels, hotels, and apartments (Eck, Clarke, Guerette, 2007; Payne, 2010), and with respect to nuisance CFS among a small set of properties (Payne, 2017). A small sample of privately owned rental properties have been found to disproportionately account for crime, with all disturbances, assaults, and drug reports associated with properties coming from 21%, 13%, and 5% of properties, respectively (Rephann, 2009).

What appears to cause crime to concentrate depends on the type of property and place being studied. Of potential importance to VHR research, one of the most salient predictors of crime at hotels and motels appears to be the cost of the room (LeBeau, 2012). However, the number of rooms, occupancy, location, and external surveillance were also important depending on the crime type being considered. Substantial crime research on rental properties focuses on property management (e.g., Eck, 2021; Eck & Madensen, 2018; Payne, 2010; 2017; Rephann, 2009), which is believed to influence crime concentration, occupants and occupancy, and crime prevention through environmental design (CPTED) concerns. The place management framework ORCA (organization of space, regulation of conduct, control of access, and acquisition of resources) presents several ways that crime is mitigated or aggravated by management decisions and quality (Eck, 2021; Eck & Madensen, 2018; Madensen & Eck, 2013; Weisburd et al., 2016, pp.46-50). Crime prevention initiatives with hotels often solicit hotel management to be crime control partners with law enforcement (e.g., Morton et al., 2019). Relatedly, surveyed hotel personnel indicated the most effective security measure was training staff to report and deal with criminal activity (Rutherford et al., 1991). Crime concentration among some properties may be the result of neighborhood characteristics in which properties reside, though a multilevel approach to this problem has only recently been applied (e.g., Deryol & Payne, 2020; Gilchrist, Deryol, Payne, & Wilcox, 2019). Lastly, crime concentration concerns and criminogenic rental properties may be explained by owners of multiple properties exhibiting the same poor management of multiple properties within neighborhoods or across multiple neighborhoods (Lee, O, & Eck, 2021). Given what is known of these other types of properties, VHRs are likely to produce greater crime than non-rented residential properties, and some VHRs may produce a disproportionate amount of all VHR crime.

Rental Properties and Crime: VHRs

Despite vacation home rentals being characterized as criminogenic (Binns & Kempf, 2021, pp.15-23; Clayton, 2019; Oh, 2014; Plohetski, 2017; Wright, 2017), research has been slow to test this characterization.[11] A potential obstacle is that companies that list these properties may exert political influence over how they are regulated (Martineau, 2019). Additionally, private companies are often the purveyors of data related to vacation home rentals, creating barriers for extensive analyses.

Vacation home rentals (VHRs) are not a new phenomenon, but they are believed to be an increasingly common one for several reasons (Kathan et al., 2016; Sheppard &

[11] A systematic review of Airbnb properties aggregated 17 problematic externalities, including trash, noise, water scarcity, waste management, parties, annoyances, disputes, hostilities, prostitution, and drug issues (Hati et al., 2021, p.13). Among the 31 publications they cite for these issues, all were published since 2016.

Udell, 2016). As a company, Airbnb was launched in 2009, though several other companies comprise the home-sharing portion of the sharing economy, and personal home rentals existed prior to this (Hati et al., 2021). The advent of the internet contributing to globalization and other associated technological advances has made VHRs, and the sharing economy in general, more visible and more accessible to a greater audience. Additionally, a change in cultural values and economic uncertainty within the United States has occurred. Kathan et al. (2016) indicate that many of the businesses involved in this market were founded, or experienced profit surges, after the 2008 recession. Involvement in this economy, therefore, could possibly be attributable to economic hardship encouraging attempts to profit from currently owned possessions.

Assessments of the impact of VHRs on different businesses and cities are ongoing, but data concerns exist. Due to regulatory difficulties (Coles et al., 2017; DiNatale et al., 2018), measuring the growth of VHRs accurately is nearly impossible. In most cities, renting out a structure requires city permitting, particular land use designations, and renter's insurance, but property owners may illegally rent their property, circumvent the authorities, and be missing from official statistics (Swiatecki, 2019). For this reason, using local government data may be problematic when assessing the relationship between VHRs and crime. An alternative is to use property data from one of the most prominent VHR online platforms: Airbnb.

Most studies that have analyzed VHRs have used data on Airbnb listings, and most studies assessing VHRs and crime have only recently been published. Recent publications have failed to include quantitative research in this area (Binns & Kempf, 2021, p.23). Table 2.1 below provides all quantitative studies to date that assess VHRs and crime–not necessarily from the perspective of VHRs causing crime.[12] Most of the studies presented involve spatial analysis. Articles are sorted on the basis of publication year. Results include positive associations (Maldonado-Guzmán, 2020), no associations (Lee et al., 2020), or mixed findings (Roth, 2021b). In some instances, studies found both a positive association in some geographic areas, and negative associations in others (Xu et al., 2019). Listing type, such as whether the entire property was rented or an individual room on the property, appeared to be an important consideration. Individual room properties (whether the room was shared or not) were typically found to be positively associated with crime, or have a greater positive association with crime than when the entire property was rented (Roth, 2021b; Maldonado-Guzmán, 2020; Van Holm & Monaghan, 2021; Xu et al., 2019).

Table 2.1. Previous Research on VHRs and Crime

Study	**Location**	**Methods**	**Results**
Yang, Tan, & Li (2019) [1]	USA, Nationwide	Binary Logit, (Vacation Trips)	The crime rate in cities decreased guests' likelihood of staying at VHRs
Xu et al., 2019 [2]	Florida	GWR	Shared rooms=pos and sig; Private room/entire house=neg; exceptions existed in certain counties.
Han & Wang, 2019* [3]	NY City, NY San Fran., CA	DID	For non-commercial home sharing, there was a positive and significant association with weapon crimes, for drug crimes, and for the overall crime rate.
Maldonado-Guzmán, 2020 [4]	Barcelona, Spain	OLS and GWR	Shared rooms had greater associations with crimes against property and people; pos/sig for all

[12] Table 2.1 excludes Reinhard (2021) as the results presented in the publication are an incomplete version of what is presented in Chapter III. The table also excludes reviews (e.g., Hua et al., 2020).

			however.
Lee et al. (2020) [2]	Florida	OLS, GWR	VHRs not significant predictor in counties.
Van Holm & Monaghan, 2021 [3]	Portland, OR; Nashville, TN; New Orleans, LA	Corr.; Panel Models	Correlations are positive and sig, but weak. Listing type matters for suspicious persons; entire homes and private rooms = decrease; shared rooms = increase. Pos/Sig results to revelry & property crimes. No relationship to sex crimes.
Roth, 2021b [5]	Austin, TX	NBR	Entire homes not sig related to crime; Private rooms pos/sig to alcohol offenses, not to acquisitive or disorder
Roth, 2021c [6]	309 Cities, TX	NBR	Airbnb density pos/sig for larceny, simple assault, drunkenness, disorderly conduct, NOT to burglary. Effects were small.
Garcia, Miller, & Morehouse, 2021 [3]	LA County, CA	DID	A law regulating VHRs decreased public intoxication CFS, did not affect party complaints or noise complaints.
Ke et al., 2021 [4]	Boston, MA	DID	The frequency of properties were positively associated with crime, though the number of reviews were not
Xu et al., 2021 [7]	Orlando, FL	Multiple spatial econometric models	Crime was negatively and significantly associated with VHR performance (revenue per available room), though the degree varied by crime type and property type

***** This paper is a working paper associated with the 2019 International Conference on Information Systems (ICIS).
Units of analyses are: [1] trips and travelers; [2] counties; [3] variable series; [4] neighborhoods; [5] Census tracts; [6] cities; [7] peer-to-peer accommodations (VHRs)

Studies presented in Table 2.1 used varied methods and analyses. The kinds of analyses included geographically weighted regression (GWR; Xu et al., 2019), regression models with spatial lag variables (Roth 2021b; 2021c), panel modelling (Van Holm & Monaghan, 2021), and difference-in-difference approaches (Ke et al., 2021; Han &

Wang, 2019). The crime types considered among these studies include aggregations of total crime (Lee et al., 2020), violent crime (Maldonado-Guzmán, 2020; Xu et al., 2019; Yang et al., 2019), property crime or acquisitive crime (Han & Wang, 2019; Maldonado-Guzmán, 2020; Roth, 2021b; Van Holm & Monaghan, 2021; Xu et al., 2019), personal crimes (e.g., assault, sex crimes; Han & Wang, 2019), sex crimes (Van Holm & Monaghan, 2021), substance crimes (e.g., drug crimes, alcohol crimes; Han & Wang, 2019; Roth, 2021b), suspicious persons (Van Holm & Monaghan, 2021), disorder and revelry (e.g., noise complaints, intoxicated persons, indecent exposure; Roth, 2021b; Van Holm & Monaghan, 2021), and weapon crimes (Han & Wang, 2019). Garcia, Miller, and Morehouse (2021) analyzed individual offense types: party complaints, noise complaints, and public intoxication. Lastly, Roth (2021c) analyzed the five individual crime types of burglary, larceny, simple assault, public drunkenness, and disorderly conduct. Although more specification was present in the study by Roth, some crime types and considerations were still missing.

Because of the interest in VHRs for tourism research, several studies were conducted by tourism scholars (Yang et al., 2019; Xu et al., 2019); these researchers' interests and methods were different than criminologists. For example, Yang et al. (2019) considered UCR violent crime data in cities as one variable for vacation trips to certain cities. They included variables such as the presence of cultural activities and how many types of social media guests used. The interest on vacation trips with crime measured in this manner is different from criminologists' interest in whether the rental properties are criminogenic (e.g., Roth, 2021b; 2021b).[13] Garcia et al. (2021) is presented in Table 2.1

[13] Caution should be used when directly comparing studies in Table 2.1. First, the FBI and BJS regularly caution against UCR data comparisons between cities (e.g., FBI, 2013; 2017). Second, crime types should

because if regulations affecting VHRs appeared to decrease crime, the assumption is that VHRs are associated with crime.

While Table 2.1 presents original quantitative research, other sources of information are not included in the table. Binns and Kempf (2021, pp.17-23) present more than 20 news articles about crime in VHR properties. These articles present instances in which hosts or guests were victims and offenders. The crimes include kidnapping, homicide, drug offenses, sex crimes, and theft, among others. Other non-peer reviewed sources, such as ongoing research about Airbnb guest problems (Fergusson, 2021), identified a combination of criminal and non-criminal issues that guests have experienced and expressed through over 120,000 guest complaints indicated on social media. These issues include scams, discriminatory practices, unsafe conditions, and customer service problems.

Additionally, some hosts are mindful about how their properties may be used criminally. There is evidence that some rental property hosts share information about how to prevent sex crimes at their properties (Thulemark, Cassel, & Duncan, 2021). Hosts suggested using external security cameras, policies against unlisted visitors, and not allowing locals to use their properties. While host and guest reviews initially appear like a mechanism to warn others about criminal or problematic persons, hosts expressed concern about leaving bad guest reviews because they feared retaliation (Thulemark, Cassel, & Duncan, 2021, p.2). Neighborhood residents may be opposed to these rental properties due to crime concerns, or on the basis of economic and cultural concerns

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generally be disaggregated (Andresen & Linning, 2012; Hewitt, 2021). The disaggregation prevents smoothing and appropriately distinguishes crimes that are substantively different. For example, violent crimes include forcible rape and aggravated assault, but there is a *shadow of sexual assault hypothesis*, not a shadow of assault hypothesis (Ferraro, 1996).

(Camprubi & Garau-Vadell, 2021; Jordan & Moore, 2018).

There are various theories and mechanisms for how VHRs are associated with crime. Among the studies that sought to understand properties or densities of properties as criminogenic, crime pattern theory (Roth, 2021c; Xu et al., 2019), routine activity theory (Han & Wang, 2019; Maldonado-Guzmán, 2021; Roth, 2021b; 2021b; Van Holm & Monaghan, 2021; Xu et al., 2019), and social disorganization theory (Roth, 2021b; Xu et al., 2019) have been considered. Outside of environmental crime theory, VHR studies considered crime because of how crime, and VHRs if found criminogenic, could reduce home prices or home prices in neighborhoods (Garcia, Miller, & Morehouse, 2021; Lee et al., 2020). Binns and Kempf (2021) suggest different kinds of mechanisms as well, depending on whether the concern is centered on criminal guests, criminal hosts, or the effect of criminal properties on neighborhoods.

Crime Theory and Mechanisms

Crime is not random (Eck & Weisburd, 1995; Sherman et al., 1989); it is also a concentrated phenomenon: concentrated among certain facilities (Cozens et al., 2019; Lee et al., 2021), in certain places (Lee et al., 2017; Weisburd et al., 2016, pp.18-28), at certain times (Curiel, 2021), against certain victims (Farrell & Pease, 2017; Pease, Ignatans, & Batty, 2018) and by certain offenders (Braga, 2012; Eck et al., 2017).[14] Within facility types, even risky facilities' (Eck, 2021; Lee et al., 2021) have observable concentrations, and rental properties are no exception: a small proportion of rental

[14] Weisburd et al. (2016, p.48) suggest 10 explanations for why crime is concentrated. The explanations, non-exhaustively, include concepts presented in crime pattern theory (e.g., crime attractors and generators), repeat victimization, physical design concerns, and place management issues.

properties often disproportionately account for more crime (Rephann, 2009). In order to understand why crime is not random, environmental criminology is often used. This section discusses the field of environmental criminology more generally before discussing the theories individually and how they may relate to VHRs.

Environmental criminology includes the routine activity perspective (Andresen & Farrell, 2015; Cohen & Felson, 1979), geometric theory of crime (Brantingham & Brantingham, 1981), rational choice theory (Clarke & Cornish, 1985; Cornish & Clarke, 1987), and crime pattern theory (Brantingham & Brantingham, 1993; 1995; Brantingham, Brantingham, & Andresen, 2017). Social disorganization theory (Shaw & McKay, 1942) is often included in these discussions (e.g., Andresen, 2014; Smith, 2000) because it considers how different kinds of neighborhoods produce conditions conducive to crime (Kubrin & Weitzer, 2003), and neighborhoods are places in which opportunistic offenders meet suitable targets and victims.

Environmental criminology broadly refers to explanations for crime that consider the physical and social environment and how individuals interact with each other and the physical environment to engage in crime (Andresen, 2014). Many kinds of crime research rely on this dependence that individuals have with their immediate surroundings. One example includes crime generators and attractors, locations that disproportionately produce crime due to abundant persons or are places known to facilitate crime (Brantingham & Brantingham, 1995). The journey-to-crime literature is another example of research that relies on the dependence of individuals and their immediate surroundings (Rossmo, 1999, pp.99-110); persons navigate streets and neighborhoods during their everyday activities, interact with other people, and are able to identify opportunities to offend (Brantingham et al., 2017; Summers & Johnson, 2017). Situational crime prevention (Cornish & Clarke, 2003), burglary target selection (Addis, Evans, & Malleson, 2021; Roth & Roberts, 2017), weekly crime patterns (Curiel, 2021), and crime displacement (Guerette & Bowers, 2009) are among a myriad of other research directions that directly rely on environmental criminology.

These theories are often discussed in unison (e.g., Browning et al., 2017; Roth, 2021c; Xu et al., 2019), and some have proposed theoretical integration (e.g., Smith et al., 2000).[15] Crime pattern theory is described as a meta theory, simultaneously considering geometry theory, routine activity theory, and rational choice theory (Andresen, 2014; Brantingham, Brantingham, & Andresen, 2017). Smith et al. (2000) found five statistically significant interaction effects between sets of routine activity and social disorganization variables predicting street robbery. For example, there were interaction effects for *the distance to the center of the city* (social disorganization variable) and multiple routine activity theory variables (vacant lots; multifamily residences; bars, restaurants, and gas stations). A limitation of that study, and comparisons between these theories generally, is that the theories are often measured at different spatial scales. Smith et al. (2000) assessed models at city blocks. Routine activity theory, crime pattern theory, and geometry theory often consider street networks, addresses, and land parcels (e.g., Brantingham & Brantingham, 1981; Brantingham, Brantingham, & Andresen, 2017; Sherman et al., 1989),[16] but social disorganization theory is typically measured in

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[15] The theories that have been discussed in unison include social disorganization and routine activity theory, crime pattern theory as an umbrella term for multiple theories, rational choice theory and other environmental theories, and so forth. The theories have been discussed in integrated manners in other contexts. For example, see Felson (2017) for a discussion on the compatibility between routine activity theory, rational choice theory, and social control theory. Wilcox & Tillyer (2017), Tillyer et al. (2021) and Linning and Eck (2021) also discuss merging community theories and environmental theories.

[16] Some scholars refer to these as "micro-geographies" (Weisburd et al., 2016, pp.3-4), whereas

neighborhoods, census block groups, tracts, or at larger spatial scales (Akers et al., 2017, p.175).[17] There are exceptions, for example, attempts to consider crime pattern theory as a macrolevel theory (Groff et al., 2014). Additionally, other possible interactions have been considered involving variables in social disorganization theory and variables in environmental theories (Weisburd et al., 2016, pp.65-66). This is all to say that these theories are similar, may be interdependent, and some amount of explanatory overlap is likely present.

Routine activity theory (Andresen & Farrell, 2015; Cohen & Felson, 1979; Felson, 1995) and social disorganization theory (Kubrin & Weitzer, 2003; Sampson & Groves, 1989; Shaw & McKay, 1942) are ecological approaches that focus on concerns about guardianship, property ownership, places where victims may interact with offenders, and the characteristics of places and the crime setting rather than on individual offenders. The routine activity perspective has evolved considerably since its inception, but still considers crime as a natural outcome when motivated offenders interact with suitable targets in poorly guarded or unguarded places (Andresen & Farrell, 2015). This theory posits that individuals are opportunistic and may either search for or seize upon opportunities as they arise during everyday life. Children walking home from school may steal items from cars (Felson & Eckert, 2018), and drug transactions may more easily occur along arterial roadways (Eck, 1995). The evolution of the theory has occurred in several ways, a principal one being how guardianship, and lack thereof, are considered and how place management operates with controllers and super-controllers (Felson,

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neighborhood theories typically use meso-geographies.

[17] Neighborhood operationalization, the modifiable areal unit problem (MAUP) and other spatial measurement issues (e.g., extrapolation between variably sized units, measurement fallacies) are discussed in Chapters III - IV.

1995; Payne, 2017; Reynald, 2018; Sampson et al., 2010).

The geometry theory and crime pattern theory rely on 10 interrelated propositions that involve how individuals navigate their environments and interact with each other during this navigation (Brantingham & Brantingham, 1981; 1993; Brantingham et al., 2017). Persons regularly travel to the same places (*activity nodes*), and the paths taken influence their acknowledgement of other people, places, and things occurring (*awareness spaces*). Persons regularly travel through places with different contexts (*backcloth*) that are separated by boundaries (*edges*). These boundaries are sometimes physical, like a river or highway, or are perceptual (Andresen, 2014, p.50). Decisions are made, both while navigating between places and while at locations, and activity patterns develop that inform what "works" and what does not work, and these decisions sometimes involve engaging in crime (*crime template*). The application of these theories has been used to examine predatory offender hunting strategies (Rossmo, 1999),[18] crime along certain street configurations (Summers & Johnson, 2017), municipal areas with permeable boundaries (Groff et al., 2014), and whether persons choose crime locations conveniently close to their homes while still being far enough to mask their identities (buffer zone hypothesis; Bernasco & Van Dijke, 2020; 2021).

Rational choice theory is the last integral theory for environmental criminology and crime pattern theory (Andresen, 2014). The theory stems from psychology and behavioral economics research regarding how individuals' decisions are largely the product of rational decisions and choices when presented with self-benefiting

[18] Similarity exists between these two crime theories and "optimal foraging theory," which is a behavioral ecology framework used to understand how searches are conducted and targets (such as a food source) are identified. Vandeviver et al. (2019) provide a review of this literature-it is outside of the scope of this dissertation.

opportunities (Clarke & Cornish, 1985). Many related concepts were adapted to criminology, including the notion that offenders' decisions are the product of their bounded rationality (March, 1978); guesses occur, and individuals make choices with a variably imperfect understanding of the circumstances in which the decisions are made. Rational choice theory, or opportunity and consequence considerations more generally, are an assumption made in many other crime theories (e.g., RAT [Cohen & Felson, 1979], social bond theory [Hirschi, 1969], deterrence theory [Stafford & Warr, 1993]).[19] The theory places importance on modelling offender behavior and decision-making, for example, to understand crime scripts (Cornish, 1994), or prevent terrorism incidents (Clarke & Newman, 2006). Rational choice theory, along with RAT and crime pattern theory, also informs situational crime prevention (SCP; Cornish & Clarke, 2003, p.49). SCP is a collection of action-oriented techniques meant to prevent offenders from seizing crime opportunities in specific settings (Clarke, 1983; Cornish & Clarke, 2003). These techniques fall within categories of increasing the effort, increasing the risks, reducing the rewards, reducing provocations, and removing excuses for engaging in crime.

Social disorganization theory (Shaw & McKay, 1942) is one of the most studied crime theories, and it considers neighborhood processes as the principal causes of crime (Kubrin & Weitzer, 2003; Pratt & Cullen, 2005; Sampson & Groves, 1989; Weisburd et al., 2016). Social disorganization variables are also among the strongest meso and macro-level predictors of crime (Pratt & Cullen, 2005). The theory is often considered to stem from concentric zone theory and Chicago in the early 20th century (Akers et al., 2017),

[19] For additional reading on the contributions of rational choice theory and how the theory interacts with others, see: Akers et al. (2017), Andresen (2014), Cornish and Clarke (1987; 2003), Addis, Evans, and Malleson (2021). Friedman and Hechter (1988) and others present information about how (sociological) rational choice theory bridges the gap between micro and macro units of analyses.

though some would posit that Quetelet originated the ideas in the 19th century (Andresen, 2014), or that it comes from Durkheim's work regarding solidarity in societies (Bellair, 2017). It has been updated and adapted since this time in various ways (see e.g., Markowitz et al., 2001; Sampson & Groves, 1989; Sampson et al., 1997). These evolutions have considered more nuanced ways of measuring the theory as distinct from community structure (Sampson & Groves, 1989), how fear and disorder interact with crime within neighborhoods (Markowitz et al., 2001), or how the theory influences neighborhood willingness to intervene and perceptions of trust (Sampson et al., 1997). Generally, the neighborhood processes considered for social disorganization theory involve the racial/ethnic composition of residents, measures of socioeconomic status or concentrated disadvantage, and residential instability. Concentrated disadvantage is typically understood to include considerations about poverty, lack of education, family disruption, and unemployment, whereas residential mobility often involves whether residents' housing are geographically stable in neighborhoods (see e.g., Patterson, 1991; Pratt & Cullen, 2005).[20]

In VHRs the structure and structure owner may remain constant, but residents of the structure change regularly as guests move into and out of the property. The tempo, timing, and rhythm (Cohen & Felson, 1979) of activities for such guests will vary from those of the activities of permanent residents. While traditional residential structures often have a homeowner, or a long-term renter, occupying the structure who acts as a guardian with personal responsibility to monitor the area (Felson, 1995), VHR occupants

[20] Thousands of publications discuss social disorganization theory in varying capacities. The following publications present detailed accounts of the theory's history, variables, results, and future directions: Akers et al. (2017), Andresen (2014), Bellair (2017), Kubrin (2009), Kubrin and Weitzer (2003), Markowitz et al. (2001), Pratt and Cullen (2005), Weisburd et al. (2016).

do not have this personal responsibility, and VHR owners may not be on the premises. In some cases, VHR owners may maintain multiple properties and live a great distance from the property (Arvanitidis et al., 2020), which complicates supervision; owner distance from properties is often associated with more crime (Rephann, 2009). VHR owners may stress economic goals over crime control, and VHR guests may leave the structure largely unoccupied throughout their stay, leaving it as an unguarded location and suitable target for residential burglary (Roth & Roberts, 2017). After finding that rental properties were positively associated with residential burglary and larceny compared to homeowner-occupied residences, Roth (2019) suggested that the former may not be maintained as well or that they may otherwise exhibit signs of disorder compared to the latter. These sorts of cues can make the difference between choosing or disregarding a property as ideal for burglary (Addis, Evans, & Malleson, 2021).

In addition to routine activity theory, social disorganization theory may be used to explain potential interactions involving VHRs and crime in neighborhoods. Social disorganization theory emphasizes the importance of "community" in neighborhoods (Sampson & Groves, 1989; Sampson et al., 1997). Neighborhoods with economic disadvantage, high residential turnover, and greater racial heterogeneity will be less cohesive socially, and this lack of cohesion affects residents' desire to look out for one another or establish informal rules that help govern what is and is not permissible. Socially disorganized neighborhoods are unable to identify and solve chronic issues, such as sustained disorder and crime (Kubrin & Weitzer, 2003). While social disorganization theory has a place component (Andresen, 2014), which is typically neighborhoods, an important aspect of the theory is the formation and utilization of social ties and social capital between residents. These social resources also demonstrate an important divergence from other theories (Kubrin & Weitzer, 2003).

From a social disorganization viewpoint, occupant instability, with residents coming and going from VHRs, decreases guardianship capability because local long-term residents are unable to determine who is a legitimate residence user. For example, if a burglar tries to gain entry to a VHR property, local neighbors may mistake the burglar for a legitimate VHR occupant. VHR occupants may also seize upon opportunities they observe around the property they are renting and burglarize other nearby properties. This phenomenon is often observed when neighborhood residents do not know each other because they do not interact with neighbors socially or as part of their everyday routines (Browning et al., 2017). The effect of VHR presence on burglary, therefore, may operate also at the neighborhood level, rather than just the individual property level.

A second mechanism through which VHRs may contribute to crime relates to VHRs being used to host parties, leading to large gatherings of neighborhood outsiders, and substance-related crime and disorder (Clayton, 2019; Oh, 2014; Steer, 2018; Yuhas, 2015). While there is limited research testing that assertion, Xu et al. (2019) found a positive association between shared-room rental lodgings and both property and violent offenses. Roth (2020) also detected a significant, positive relationship between alcohol offenses and VHRs that rented private rooms. Additionally, crime associated with gatherings of outsiders within VHRs may be exacerbated by properties with incapable or absentee landlords. For example, Rephann (2009) found that disturbances and drug offenses at rental properties were all positively associated with landlord remoteness from the properties. Landlords who owned more units had more disturbance calls at their residences as well, presumably because they were less able to effectively monitor them. While they are not VHR properties, other kinds of rental properties have also been found to provide ideal locations for individuals selling drugs, with sellers and buyers contributing to numerous and varied other kinds of offenses (e.g., Eck, 1998; Eck & Wartell, 1998).

Present Research

All of the research presented to this point has been useful, in a general sense, for a comprehensive examination of VHRs and crime; however, additional research is of unique interest to each of the next three chapters. Most of this uniquely focused research is presented at the beginning of each chapter, and includes neighborhood operationalization concerns for Chapter III, modifiable areal unit problem (MAUP) considerations and robustness checks for spatial data for Chapter IV, and time-series and seasonality issues for Chapter V. Each of the aforementioned literatures benefits from understanding crime, environmental crime theory, and crime research pertaining to rental properties and VHRs.

This dissertation's use of multiple units of analysis (block groups, egohoods, months) to address hypotheses across studies warrants addressing how this may influence results. Associations between the same set of variables may change when studied among different units of analysis like individuals versus communities (e.g., poverty and crime, Patterson, 1991; Sharkey et al., 2016), and when assessing relationships in larger areas compared to smaller areas (counties, Xu et al., 2019; tracts, Roth, 2020). There are several possible explanations, including that larger areas present greater opportunity for spatial variation of phenomenon that require space to occur (Patterson, 1991). A city's crime rate may not reflect the crime in any individual neighborhood of the city. Additionally, a crime dense area may be surrounded by low crime areas (Payne & Gallagher, 2016), obscuring the situation when a larger spatial unit of analysis is used. In other words, "lower order geographic variability" occurring in smaller units of analysis within a larger unit of analysis may lead to the conclusion that crime is stable if smaller units have both increasing and decreasing crime trends within the larger unit of analysis (Weisburd et al., 2009, p.20). These considerations appear throughout the remainder of the dissertation in various forms (e.g., MAUP in Chapter IV, and temporal aggregation issues in Chapter V).

III. STUDY ONE: VHRS AND CENSUS BLOCK GROUPS[21]

Background

The use of census block groups (CBGs) for this chapter and the consideration of *neighborhood* disadvantage and comparisons warrant first addressing the idea of neighborhoods. This chapter considers CBGs as neighborhoods, and considers rental properties, vacation home rentals (VHRs), crime concerns, and social disorganization constructs within geographically exclusive areas. Geographically relevant study results are often contingent on how neighborhoods, or spatial boundaries in general, are measured (Lawton, 2018; Song et al., 2013). Phrased differently, variables may be differently associated depending on the unit of analysis (Patterson, 1991; Sharkey et al., 2016). As noted in Chapter 2, VHRs may influence crime in many ways, including ways that affect buildings adjacent to properties and neighborhoods where the property is located (Binns & Kempf, 2021).

Many constructs and ideas in the social sciences have contested definitions, which in turn results in varied operationalizations. While this section considers neighborhoods as being one of these constructs (e.g., Hipp & Boessen, 2013; Nicotera, 2007; Sampson, 2011), this discussion could be extended to include numerous other concepts that routinely present challenges for researchers.[22] Additionally, living in a neighborhood may not yield useful information about what that means and how to measure it; people in neighborhoods regularly have subjective understandings about neighborhood boundaries

[21] Parts of *Chapter III* appear in the publication:
Reinhard, D. (2021). The influence of vacation home rentals on neighborhood crime and disorder. *American Journal of Criminal Justice*, 1-17. https://doi.org/10.1007/s12103-021-09635-8

[22] For example, measuring homelessness (Cordray & Pion, 1991). Defining homelessness is often complicated by the dynamic nature of episodic homelessness, marginal accommodations, the phenomena of "couch surfing," government assisted housing, and long-term shelters.

(Hipp & Boessen, 2013; Sampson, 2011).

Neighborhood is a controversial concept in part due to measurement issues (Hipp & Boessen, 2013; Nicotera, 2007; Sampson, 2011). Several aspects of measurement are regularly used and discussed, but the manner in which a variable is defined (conceptualized) and the manner in which the variable is interpreted as varying (operationalized) are important. The criminological literature uses a myriad of definitions of neighborhood, though the present study will first separate neighborhoods in terms of *neighborhood effects research* and environmental criminology or *crime science research* (Clarke, 2010).[23] It is also worth noting that neighborhood research, and the associated complications with neighborhoods, are also issues in other disciplines, such as demography, sociology, and psychology (Nicotera, 2007).

When considering the neighborhood effects research, there are at least two classes of thought regarding neighborhoods. The first class focuses on the social interactions involved among residents living and interacting near one another. For example, Sampson (2011, p.228) uses "a variably interacting population of people and institutions in a common place." This class of thought considers the interactions among residents within overlapping "common places." Sampson (2011, p.229) argues this approach is contrasted against the "menu of ecological units of analysis from which to choose" that many other studies use; it may be impossible to have a single correct definition and measurement for neighborhoods. The approach suggested involves "ecometrics" (ecology-metrics), with considerations about interrelated social processes that occur. These processes include the

[23] Overlap exists between these areas. For example, within neighborhood effects research, neighborhood resident interactions have been studied from a social network perspective and considering social capital. Within environmental criminology, neighborhood resident interactions may be measured using routine activity or crime pattern theory concerns.

social network, norms and collective efficacy, organizational infrastructure, and activity patterns (Sampson, 2011). One should consider that it is not only neighborhood residents interacting in a neighborhood; within a neighborhood there will be non-residents present who are socially or geographically adjacent. Social adjacency occurs with a recreation center. For example, it occurs when individuals gather for an activity not based on where they live, but based on mutual participation in an activity or event. Neighborhood outsiders and insiders have been considered for some time, and prevention efforts may need to be tailored to concerns regarding one or the other (Bowers & Johnson, 2015; Brantingham & Brantingham, 1995). Neighborhoods then may not be simply the sum of their parts, if parts are only considered in terms of individuals or addresses. It is for this reason that some of Sampson's (2011) work involves understanding how individuals choose neighborhoods non-randomly, and mobility within a metropolitan area does not obey standard perceptions of geographic adjacency. For example, families may move to different neighborhoods because of employment, social ties, particular amenities, and so forth.

The second class of thought for neighborhoods is concerned more with geographic boundaries. This second class may further be differentiated by operationalizing neighborhoods as having non-overlapping and overlapping boundaries (Hipp & Boessen, 2013). Historically, there has been more support for using non-overlapping boundaries. For example, zip codes, census block, block groups, and tracts all represent distinct, mutually exclusive areas with clearly defined boundaries (Nicotera, 2007; Sampson et al., 2002). Census data is often used because they are inexpensive and easy to access, despite only addressing the physical nature of neighborhoods (not necessarily capturing the social processes) and doing a poor job of approximating "actual" neighborhood boundaries (Nicotera, 2007, p.31-33).

While one understanding of neighborhoods has been considered, some scholars posit that considering neighborhoods requires both the social and physical aspects (Nicotera, 2007). Neighborhood is a combination of both the "environment" and the "place," with the former being the more objective physical conditions and the latter being the lived experiences of insiders who understand more nuanced realities within the location.[24] Support exists also that neighborhoods and the residents therein are subjected to both close and distant processes (Nicotera, 2007, p.29). Residents' perceptions from adjacent neighborhoods influence the social processes within a neighborhood, and being affiliated with a particular neighborhood may have harmful consequences for residents (Anderson, 2019).

Environmental criminology, and the recent delineation of crime science (Clarke, 2010) has a somewhat different perspective about neighborhoods. Neighborhood is a founding principle of the study of crime at places (Weisburd et al., 2009) but diverged in the same way that social disorganization theory diverges from environmental criminology. Some scholars note that the study of crime places in the 18th century is responsible for the study of crime generally (e.g., Rossmo, 1999; Weisburd et al., 2009). While social disorganization theory may have originated studying crime places in the 20th century, it may be more accurate to now categorize social disorganization theory and collective efficacy theory as neighborhood theories, while crime pattern theory and other crime-distance literatures are within environmental criminology (Andresen, 2014;

[24] Also see Eck and Madensen (2018) for a discussion of the features of places, kinds of places, and issues studying places.

Brantingham, Brantingham, & Andresen, 2016; Cullen & Kulig, 2018).

One reason that neighborhoods became less popular within environmental criminology is due to an increased awareness of and capability to measure spatial variability in crime data at smaller units of analysis. As smaller geographic units of analysis are used, greater crime concentration is observed (Lawton, 2018; Payne & Gallagher, 2016). The logic is as follows: to understand crime at "places," individuals must analyze the smallest geographic area that provides the greatest spatial specificity. Smaller spatial units of analysis are likely to decrease within-group heterogeneity and increase between-group heterogeneity. By using larger areas, there is a failure to identify the nuanced manner in which fluctuations occur in smaller areas within the larger area (Payne & Gallagher, 2016; Weisburd et al., 2009). This has also spawned the specification of differently shaped hot spots (Eck, 2005). Hundreds of studies have been conducted to analyze crime at street addresses, street segments, streets, city blocks, street clusters, census block, block groups, and tracts in order to understand how boundary consideration and geographic unit size influences the results of crime studies. Concerns exist over the most appropriate spatial unit of analysis (Lawton, 2018), or whether variables need to be compared at multiple spatial units (Boessen & Hipp, 2015).

A second reason that neighborhoods are less popular as a unit of analysis within environmental criminology may be that it complicates possible interventions and crime prevention initiatives. If a neighborhood is composed of numerous residences, streets, sidewalks, parks and businesses, the neighborhood presents numerous different elements that must be considered for target suitability, offender motivation, guardianship, and temporal activity use (Cohen & Felson, 1979). Environmental criminology is often posited as being more actionable than other explanations of crime because crime events may be easier for practitioners to influence (Payne & Gallagher, 2016). Crime hot spots may only occur in one part of a neighborhood, like at a specific address (Payne, 2017a), but it is still an open question how much crime at one geographically confined location will affect an entire neighborhood. It appears to depend. It may require differentiating types of crime (Andresen & Linning, 2012), and whether the neighborhood is being considered as an environment or as a place (Nicotera, 2007). While not satisfactory, neighborhoods are likely best operationalized as being of different sizes depending on unique characteristics of each neighborhood (Hipp & Boessen, 2013). However, being differently sized presents its set of issues regarding statistical comparisons generally and geographic problems specifically (e.g., MAUP; Andresen, 2014; 2018).

However, numerous problems exist with the logic of smallest possible spatial units of analysis. Relatedly, problems also exist with the granular specification of crime types, or time of crime. A principal issue is that crime is rare (Felson & Eckert, 2018; Payne & Gallagher, 2016; Sherman, Gartin, & Buerger, 1989), and statistical inference requires variability. A recent crime prevention intervention analysis found that crime was 52 times more concentrated at a city block intervention site than would occur if crime were random throughout the city (Reinhard, Vàsquez & Payne, 2021). However, in a small intervention site, even a high crime area has few crimes. Analyses of “micro spatial areas” (Andresen & Linning, 2012) do not have sufficient crime occurring to always allow for the disaggregation of crime types.

These considerations about neighborhoods, geographic unit size, and aggregation concerns are all relevant for the present chapter, particularly for how this study is different from others. Roth (2020) analyzes data on Airbnb properties in Austin, Texas in 2017 using 234 census tracts and analyzing acquisitive, disorder, and alcohol offenses. The present study analyzes Airbnb properties in Austin, Texas in 2018 using 602 census block groups and analyzing residential burglary, disturbances, and substance crimes. The year is different, the crime types are different, and the geographic unit of analysis is different. It is expected that by using a smaller unit of analysis, this study may provide greater clarity regarding facilities and neighborhood concerns within each area (Payne & Gallagher, 2016; Rengert & Lockwood, 2009). Both studies use a spatial lag variable (albeit created differently); however, the present study further explores vacation home rentals spatially and while considering the environmental literature regarding the law of crime concentration (Rengert & Lockwood, 2009; Telep & Weisburd, 2018; Weisburd, 2015; Weisburd, Burnasco, & Bruinsma, 2009). Additionally, the present study analyzes reported rental properties as identified by the city of Austin, Texas compared to data on Airbnb properties, many of which may not have been reported to the city (Katz, 2015; Valentin, 2020). Lastly, this chapter presents additional descriptive information on VHR properties in the city.

Chapter II presents numerous mechanisms by which VHRs may influence neighborhood crime (Binns & Kempf, 2021; Han & Wang, 2019; Maldonado-Guzmán, 2020; Van Holm & Monaghan, 2021). However, it is anticipated that VHRs will ultimately be positively associated with crime. The three hypotheses relevant to Chapter III are:

H1: Vacation home rentals will be positively associated with residential burglary in CBGs.

H2: Vacation home rentals will be positively associated with substance crimes in CBGs.

H3. Vacation home rentals will be positively associated with disturbances in CBGs.

Methods

The study is set in Austin, Texas, which was chosen due to its size and substantial tourism industry (Roth, 2020). The city is also consistently ranked among the most desirable in the United States based on the city's affordability and quality of life (Bloom, 2019). These factors likely contribute to make Austin, Texas a city with a substantial number of VHRs, providing additional confidence in one's ability to detect variation between these properties, crime incidents, and neighborhood conditions. The unit of analysis for this study is CBGs; only the 604 CBGs within the jurisdictional limits of the Austin Police Department were considered, and two were removed due to their characteristics. Following Roth (2020), the two CBGs removed for the final analysis were those corresponding to the Austin airport and the county's correctional complex, making the final sample size 602. Among the 602 CBGs used for this study in 2018, there was a median population of 1,653 persons.

Data sources

Crime Data

Crime incident data from the Austin Police Department for 2018 were used for this study. The data represent police-initiated and police calls for service leading to crime. Limitations for reported offenses and police data are present and recognized. For example, not all crimes are known to the police, and among known crimes, not all are pursued. There were 2,595 residential burglaries, 1,093 substance crimes, and 13,970 disturbances in 2018 in the study area. Location and time data were available for each crime incident; location data were used to aggregate incidents to the census block group (CBG) level. Residential burglary data only include incidents classified as burglary of a residence.[25] Substance crimes data include incidents, such as underage possession of alcohol, distribution of alcohol to a minor, possession of drug paraphernalia, and possession of a dangerous drug. Disturbance data include disturbance incidents that are not “parental” or “family” disturbances; instead, disturbances relate to noise complaints, unlawful gatherings, and ordinance violations.[26] All incidents listed geographically as occurring at any of the premises associated with Austin Police Department were removed (e.g., if geocoded to a local police station, rather than the location where the crime occurred). The crime data originated as a shapefile, meaning that geocoding had occurred prior their present use, and fewer concerns exist regarding their spatial reference (e.g., see Ratcliffe, 2004).

Vacation Rental Properties

In this study, VHR properties are represented by Airbnb properties.[27] While many Airbnb properties are vacation home rentals, not all vacation home rentals are Airbnb properties. Other companies also facilitate marketing home rentals, including VRBO, or

[25] For example, “burglary of non-residence” incidents were not included. In addition to prior research guiding these decisions (see Chapter II), a crime analyst for the Austin Police Department was consulted to ensure the scope of inclusion for various crime incident types.
[26] Parental and family disturbances were excluded out of concern that their inclusions would conflate host family disturbances with non-host disturbances.
[27] For example, VHRs may instead refer to other kinds of home shares advertised on other home sharing sites or other types of rental properties (Hati et al., 2021).

HomeAway, among others (Binns & Kempf, 2021; Jordan & Moore, 2018) and properties may be simultaneously listed on multiple platforms. Because of this, Airbnb properties should be considered a conservative estimate of the full scope of home rental properties (DiNatale et al., 2018), although they will likely be much more accurate than official local government records (Swiatecki, 2019). The extent to which Airbnb is dominant among other home sharing platforms is difficult to quantify, though by several metrics (such as billions in market valuation, profit, millions in revenue, reviews, guests served) Airbnb appears substantial compared to other similar companies (see Hati et al., 2021).[28] Data were obtained through AirDNA, a private company that documents Airbnb locations, and only properties active in 2018 were used in this chapter. The count of VHR properties were considered for these CBG analyses. Properties are differentiated into three variables for this study. "VHR:All" refers to all VHR properties, including properties in which the entire structure is rented and properties in which only a room is rented. "VHR: Structure" corresponds to only properties in which the entire property is rented. "VHR: Room" corresponds to properties in which an individual room or a shared room are rented from the property.

Short-term Rentals

The city of Austin, Texas reports short-term rentals (STR) in 2018, and the data contain geographic variables that allow them to be geocoded to census block groups. These data were downloaded from the Austin Data Portal, geocoded, and compared to the

[28] The comparison is described as difficult because comparisons are often made outside of the peer-reviewed literature and these companies span dozens of countries and thousands of cities across the world. Hati et al. (2021) notes four other systematic reviews, besides their own and note that Airbnb is the most studied home sharing platform- that may present further limitations for comparisons.

vacation home rental data. These data and the VHR data are likely not mutually exclusive; some VHRs are likely reported to the city and included in the STR data, and some STRs are not VHRs. There were 2,185 STR properties reported by the city in 2018. This variable is considered first to ascertain the extent to which city-reported rentals mirror the (presumably) unreported VHR properties. Secondly, it is considered to assess the extent to which reported and unreported (or partially reported) properties populate the same or different neighborhoods.

Bars and Nightclubs

The presence of bars and nightclubs has been previously associated with substance crimes and disturbance incidents (Twinam, 2017; Wheeler, 2019), and so were also considered for this study. Furthermore, bars may represent locations of interest for VHR occupants, and the availability of alcohol may influence those crimes (Cohen & Felson, 1979; Roth, 2020). The Texas Alcoholic Beverage Commission (TABC) provides data on alcohol-related licenses and permits issued in 2018, which were used for this study. The geocoding success rate was 99.5%, resulting in 734 unique locations in the study area; this is above commonly accepted geocoding thresholds (Ratcliffe, 2004). There are several reasons to include the presence of liquor establishments and not other facilities. A principal reason is that liquor stores are likely the most studied kind of facility (Cozens et al., 2019), which provides a greater swath of research to draw upon and confidence in the likelihood that liquor stores contribute to many types of crime (Groff & Lockwood, 2014; Teh, 2008).

Liquor stores may be the most studied for several reasons, such as the availability of data and legal requirements regarding transparency of liquor licenses. Crime has been studied, or reported, regarding the inside of (Frisbie et al., 1977; Rosay & Langworthy, 2003), around (Block & Block, 1995; Rengert et al., 2005; Roncek & Bell, 1981), and at varying distances to (Groff, 2011; Ratcliffe, 2011; 2012), multiple kinds of liquor stores, taverns, and bars. Additionally, many kinds of offenses have been analyzed among the aforementioned studies and others (e.g., Gruenewald, 2011; Livingston, 2011). On-site and off-site liquor establishments have been found to influence crime around them (Wheeler, 2019), and liquor selling facilities appear to present challenges for property managers and the broader communities in which they are located.

Socio-Demographic Variables

Similar to prior research (Mletzko et al., 2018; Roth, 2020), data from the U.S. American Community Survey (ACS) were used to operationalize social disorganization in the study area. ACS 2018 five-year estimates were used to assess the degree of concentrated disadvantage, residential instability, and racial heterogeneity in Austin, Texas. The concentrated disadvantage variable was created by summing the standardized versions of the following items, and dividing the total by four: the percent of families below the poverty line, the percent of households receiving public assistance, the percent of unemployed residents aged 16 and older, and the percent of residents aged 25 and older without a bachelor's degree ($\alpha = 0.71$). Residential instability was calculated similarly after combining the percent of the population living in a different house compared to 12 months ago, and the percent of housing that is renter-occupied ($\alpha = 0.75$). The racial heterogeneity variable was created using Agresti and Agresti's (1978) index of qualitative variation, with the following racial groups being considered: White, Black, Asian, Native American and Alaska Native, and Other. The formula below was used, with possible values ranging from 0, which indicates all residents being of the same race, to 1-1/k, with k being the number of groups considered. For this study, the maximum possible value of 0.8 would indicate a CBG with residents equally spread among all five race groups.

$$EH = 1 - \sum_{i=1}^{k} \left(\frac{n_i}{N}\right)^2$$

Figure 3.1. Index of Qualitative Variation

where:

n_i = the number of residents for each race group;

k = the number of subgroups used

N = the total number of all residents

Analytic Strategy

The distributions and characteristics of the data warranted use of count regression models. After dispersion was identified, and post-estimation tests were assessed, negative binomial regression was selected as the most appropriate method of multivariate analysis. [29] No multicollinearity issues were detected among crime variables, social disorganization, VHR, or bar and nightclub data. However, due to the spatial nature of the data, spatial autocorrelation was checked for each crime type.

[29] Four primary models were initially considered, negative binomial, Poisson, zero-inflated negative binomial, and zero-inflated Poisson. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values preferred negative binomial over all others, though the difference between negative binomial and zero-inflated negative binomial were inconsequentially similar (Hilbe, 2011); given this, the negative binomial model was selected.

Tests for spatial interdependence are warranted and commonly used when considering both routine activity theory and social disorganization theory (Kubrin & Weitzer, 2003; Mletzko et al., 2016). Moran's I is a commonly used first step to establish spatial autocorrelation (Anselin, 1996; 2003; Kubrin & Weitzer, 2003, p.394), though others exist. Moran's I is used to establish whether point data are concentrated geographically, and Nearest Neighbor establishes whether counts are concentrated within adjacent aggregated areas. Similar to previous research (Lee et al., 2017; Rephann, 2009), statistically significant clustering was found across incidents and CBGs (see Table 3.1). Phrased differently, these statistics appear to find that crime points and crime counts in CBGs (an aggregate value at a larger spatial unit of analysis) are dependent on adjacent crime and crime in adjacent block groups (Anselin, 2003, p.310). The significant values ($p<.05$) indicate a rejection of the null hypothesis of no association; points and values within CBGs are significantly clustered and interdependent compared to what would be expected due to chance.[30]

Table 3.1. Spatial Concentration Statistics

	Coef.	Z
Nearest neighbor ratio		
Residential burglary	0.45	-53.71**
Substance crimes	0.41	-41.49**
Disturbances	0.26	-170.23**
Global Moran's I		
Residential burglary	0.22	27.29**

[30] Direct interpretation of these coefficient values are not attempted as both are indices indicating the extent to which patterns of association are detected in the observed data versus data fabricated under the assumption of random spatial presence in the area(s) of interest. For greater clarity on this explanation and the notation involved, see Anselin (1996, 2003), ArcGIS Pro (2021).

Substance crimes	0.02	6.20**
Disturbances	0.18	23.76**

(**) $p < .01$.

Due to the significant clustering detected, spatial lag variables were created for each kind of offense. Spatial lag variables are increasingly used to account for spatial autocorrelation (Roth, 2020). Controlling for spatial autocorrelation helps to maintain residual independence and prevent the violation of regression assumptions (Anselin, 2003; Geniaux & Martinetti, 2018). “The spatial lag model incorporates the spatial influence of unmeasured independent variables but also stipulates an additional effect of neighbors’ crime rates” (Kubrin & Weitzer, 2003, p.394). Anselin and Bera’s (1998) equation was used to create spatial lags for each crime type, with:

$$SLag_i = \sum_{j=1}^{N} \frac{c_j}{d_{ij}}$$

Figure 3.2. Equation for Spatial Lag Variable

where

i = CBG for which the spatial lag is being calculated

j = all other CBGs

N = the total number of other CBGs (601)

cj = the number of offenses in the CBG

dij = the distance in miles between the centroids of CBGs i and j

The Haversine formula (Alkan & Hasari, 2019) was used to calculate the distance of all X, Y coordinate pairs of CBG centroids as required for d_{ij}. Lastly, the total number of households was used as an exposure variable for residential burglary models, and the resident population was used as an exposure variable for both substance crimes and disturbances.

In addition to the above models, correlations are provided to contextualize VHRs in CBGs. These correlations include the three VHR variables (All, Structure, Room), short-term rentals (STRs), median home value, median household income, count of households, and the three social disorganization variables (Table 3.5). These correlations help to form considerations about how VHRs populate neighborhoods, particularly considering STRs in the city, neighborhood affluence (as measured with home value and median income), and with respect to social disorganization variables.

Results

Descriptive Results

In 2018 there were 12,737 entire structure VHRs and 5,669 private or shared room VHRs in Austin, Texas. There were 18,406 total VHR properties including both groups of properties. Table 3.2 provides descriptive information regarding the VHR properties, distinguished on the basis of whether the VHR was for the entire structure or an individual room (for both shared and private rooms). Zero values were omitted from Table 3.2. This is done because it is unknown whether zero values occurred on the basis of missing data or true zero values. The values are mean averages; the unit of analysis is individual VHR properties, except for host variables that present information on hosts that own multiple VHRs. It is important to note that the data presented here are disaggregated based on listing type, which has not been commonly done elsewhere when considering income and tourism industry comparisons (e.g., Binns & Kempf, 2021, pp.12-13). The mutually exclusive and aggregated distinction at the bottom of Table 3.2 reports the frequency of hosts with greater than one property among only one type of property, and both properties combined. For example, among hosts of both property listing types (Full Property and Individual Room), 19.46% of hosts were associated with two or more properties. Among both types of listings, 44.99% of properties were owned by host IDs with two or more properties. Additional variable details on each of the variables from Table 3.2 appear in the Appendix.

Table 3.2. Descriptive Data on VHR Properties in 2018

	Variables	**n (full,room)**	**Full Properties**	**Individual Rooms**
	Daily Income	6596 , 2338	$328.88	$88.48
	Annual Revenue	6596 , 2338	$29544.39	$5957.09
	Security Deposit	6251 , 1548	$480.51	$259.59
	Occupancy Rate	6596 , 2324	56.03%	51.11%
	Number of Reservations	6575 , 2324	35.31	23.19
	Max Guests	12735 , 5668	5.22	2.31
	Response Rate	11095 , 4793	96.39	95.40
	Unoccupied Days	6272 , 2239	81.02	68.75
Mutually Exclusive	% of Hosts with >1	9182 , 4209	13.93%	18.53%
	% VHR owned in Collection	12737 , 5669	37.95%	39.51%
Aggregated	% of Hosts with >1	12571 (820 overlap)	19.46%	
	% VHR owned in Collection	18406	44.99%	

Table 3.3 provides descriptive information for all variables used. While the data suggest overdispersion because of standard deviation values substantially greater than mean values, models were reviewed to ensure actual dispersion was present (Hilbe, 2011). The range of values for each outcome variable was considerable and varied between 0 and 41 (residential burglary), 0 and 258 (substance crimes), and 0 and 370 (disturbances) in each CBG. Similarly, VHRs and bars were not normally distributed with considerable ranges and positively skewed mean values. The frequency of low count CBGs for the dependent variables is provided in Table 3.4. A substantial percent of CBGs contained zero residential burglaries (23.3%), substance crimes (48.2%), and disturbances (14.6%). Incident frequency was also concentrated such that the 20% most incident prone CBGs across the city contained 78.4% of substance crimes, 58.6% of disturbances, and 57.7% of residential burglaries.

Table 3.3. Variable Summaries (N=602 CBGs)

	Count	Mean	Median	SD	Min	Max
Residential burglaries	2,630	4.37	3.00	5.10	0.00	41.00
Substance crimes	1,356	2.25	1.00	11.14	0.00	258.00
Disturbances	14,440	23.99	14.00	30.06	0.00	370.00
VHRs (All)	18,406	30.11	14.00	50.92	0.00	772.00
VHRs (Structure)	12,737	21.16	8.00	42.37	0.00	651.00
VHRs (Room)	5,669	9.42	6.00	11.68	0.00	115.00
Short term rentals	2,185	3.63	1.00	12.76	0.00	224.00
Bars	929	1.54	0.00	8.45	0.00	195.00

Conc. Disadvantage	---	-0.02	-0.19	0.73	-1.09	3.10
Residential instability	---	0.33	0.31	0.19	0.00	0.84
Racial heterogeneity	---	0.35	0.36	0.18	0.00	0.71

Table 3.4. Offense Distribution per CBG

Incidents per CBG	Residential burglary		Substance crimes		Disturbances	
	N	%	N	%	N	%
0	140	23.3	290	48.2	88	14.6
1	71	11.8	98	16.3	18	3.0
2	59	9.8	84	14.0	16	2.7
3	64	10.6	42	7.0	24	4.0
4	59	9.8	16	2.7	12	2.0
5	42	7.0	27	4.5	21	3.5
6	36	6.0	8	1.3	14	2.3
7+	131	21.8	37	6.1	409	67.9

The four maps below (Figures 3.3-6) provide choropleth maps of VHR properties and crime incidents in Austin, Texas in 2018. Each map presents counts of the respective crime type, with block groups visualized using manual intervals. Increased frequency of offenses corresponds to darker colored CBGs. Arterial roadways are displayed in each map, and arterial is operationalized as roadways with posted speed limits greater than or equal to 55 miles per hour. This is done for spatial referencing purposes.

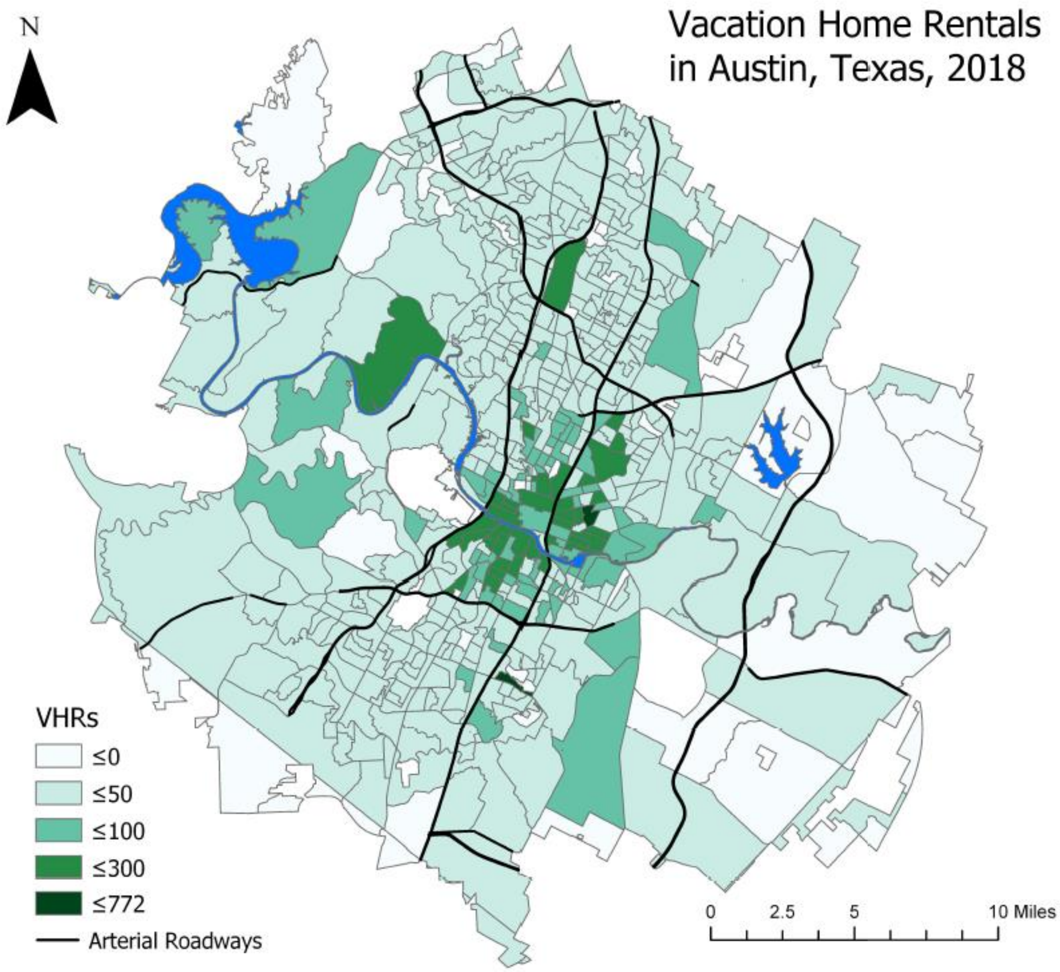

Figure 3.3. Choropleth Map of VHR Properties in Austin in 2018

Figure 3.3 presents VHRs present in Austin, Texas in 2018. VHRs in the city are largely concentrated in the downtown core of Austin, Texas.[31] Each block group contains between 0 and 772 VHR properties. While VHRs appear to be largely concentrated in the downtown part of the city, a dichotomous variable to differentiate downtown properties did not significantly contribute to statistical models for any of the three crime types used in this study. While short-term rental (STR) properties are not visualized here, there is a strong, significant and positive correlation between STRs and VHR: All (r=.86, p<.01).

[31] All VHRs are visualized in Figure 3.1. VHR listings are distinguished for multivariate models below.

In other words, a map of STRs is highly similar to Figure 3.3.

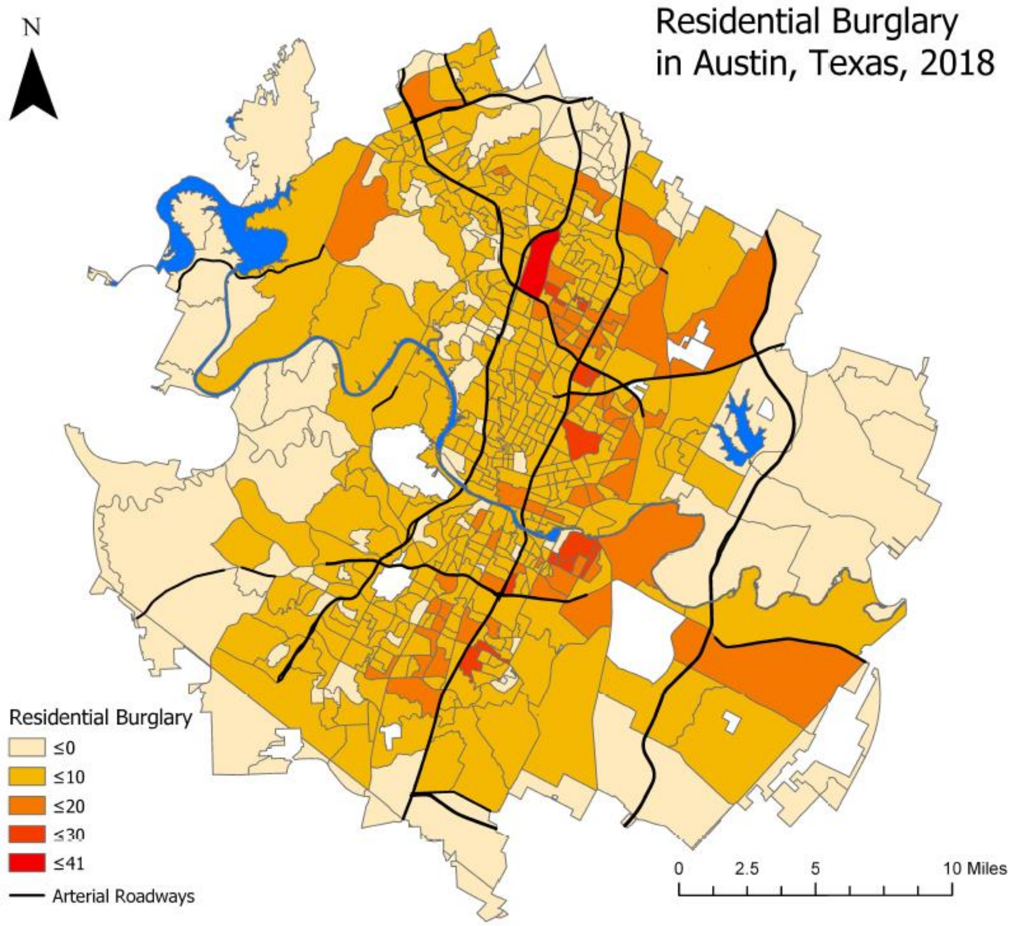

Figure 3.4. Choropleth Map of Residential Burglary in Austin in 2018

Figure 3.5 presents the locations of residential burglaries, which are the most dispersed crime type in frequency and geographic location. Each block group contains between 0 and 41 residential burglaries, and these burglaries are spread throughout the city more so than substance crimes and disturbances.

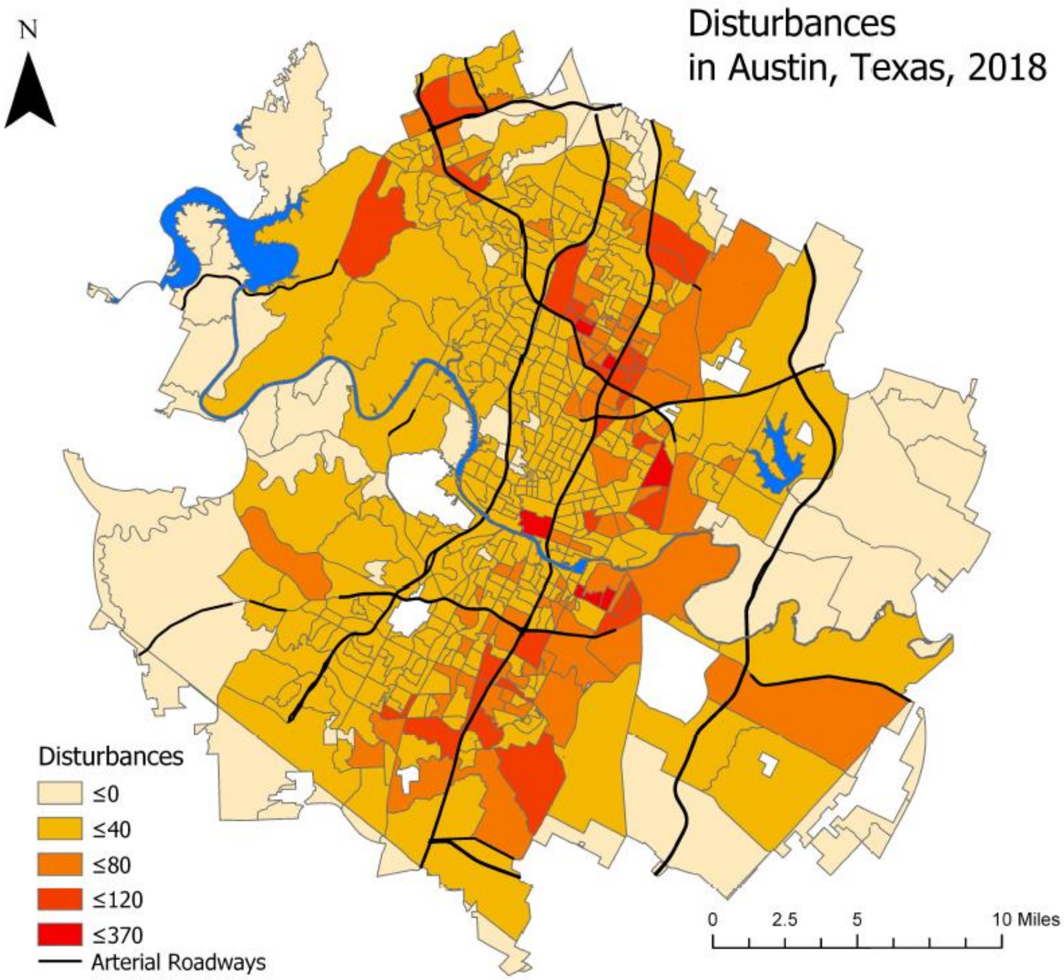

Figure 3.5. Choropleth Map of Disturbances in Austin in 2018

Figure 3.5 presents the location of disturbances in Austin, Texas in 2018. Disturbances tend to be concentrated in CBGs adjacent to arterial roadways that bisect the city from North to South. There are between 0 and 370 disturbances in each CBG.

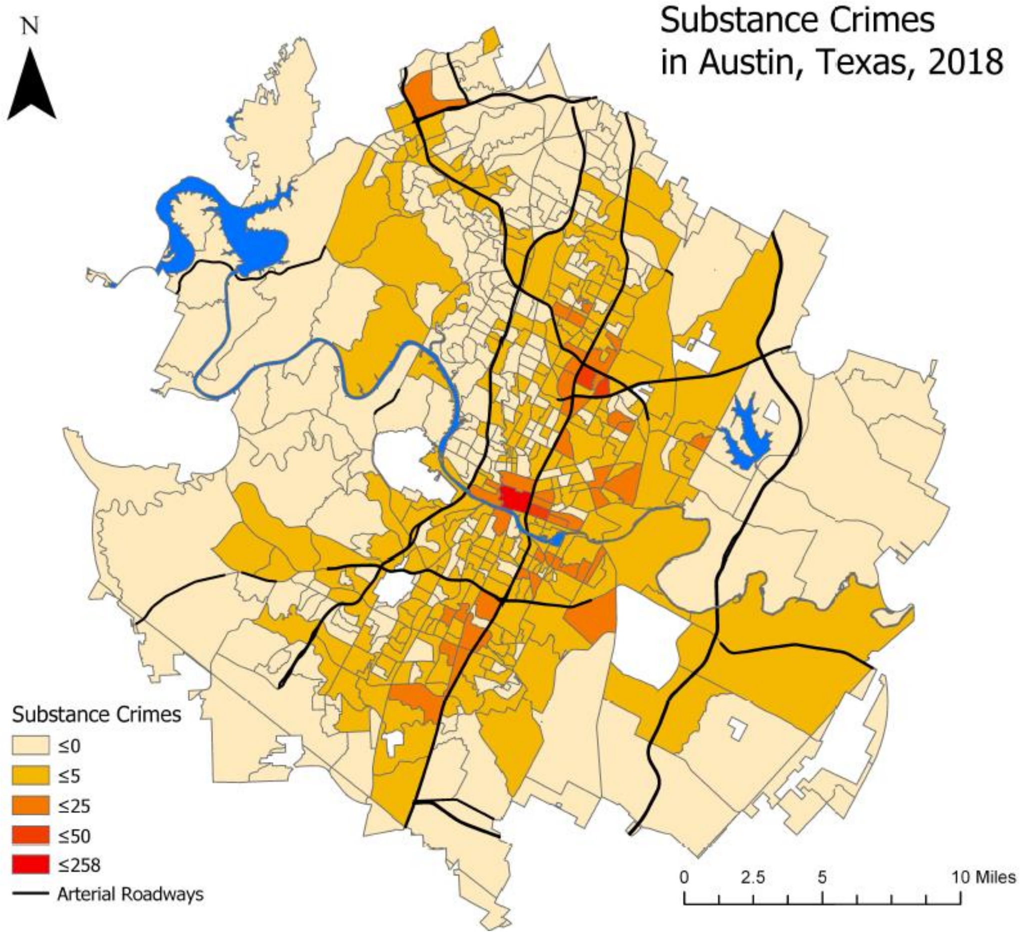

Figure 3.6. Choropleth Map of Substance Crimes in Austin in 2018

Figure 3.6 presents substance crimes in the city in 2018. Substance crimes are more concentrated than disturbances or residential burglaries, and the greatest frequency occurs in the downtown core, approximately in the middle of Figure 3.6. This CBG, and those immediately adjacent to it, are also the principal location of alcohol establishments in the city.

Multivariate Results

Correlations are presented in Table 3.5 for neighborhood home value, household income, different property types, social disorganization variables, and the total number of households in CBGs. There are 2,185 STRs, 18,450 VHRs (total), 12,737 VHRs (structure), and 5,669 VHRs (room).[32] Home value in neighborhoods was positively and significantly associated with VHR: All ($r=.08$, $p<.10$) and VHR: Structure ($r=.14$, $p<.05$), but non-significantly associated with VHR: Room ($r= -.05$, $p>.10$). Median household income was significantly and negatively associated with all VHR variables, but with VHR: Room ($r= -.26$, $p<.05$) more than the other VHR variables. VHR: All was positively and significantly associated with both VHR: Structure ($r= .43$, $p<.05$), and VHR: Room ($r= .40$, $p<.05$), but less so than the association between VHR: All and short-term rentals (STRs). STRs were highly correlated with VHR: All ($r=.86$, $p<.05$) in a positive and significant manner. Regarding the social disorganization variables, concentrated disadvantage ($r= -.11$, $p<.05$) and residential instability ($r= -.12$, $p<.05$) were both significantly and negatively associated with VHR: Structure, but not significantly associated with VHR: Room. Racial heterogeneity was positively and significantly associated with all VHR variables, but slightly more so with VHR: Room ($r= .25$, $p<.05$) than the others. Lastly, the total number of households in CBGs was positively and significantly associated with VHR: All ($r= .15$, $p<.05$), but non-significantly associated with the other VHR variables.

The correlations in Table 3.5 suggest neighborhood differences may be present regarding VHR: Structure and VHR: Room. This is observable through the social disorganization variable differences and the affluence variables (home value and household income). Less disadvantaged neighborhoods with less residential instability

[32] The frequency of total VHRs includes a small count of hotels or other rental accommodations listed on the Airbnb website that were not entire residential structures or rooms in residential structures.

tend to have more entire structure VHRs, though those distinctions do not appear to matter, on average, for room-only VHR properties. While the counts are substantially different, it is also surprising how strong the association is between VHR: All and STRs, especially given the much weaker associations for VHR: Structure and VHR: Room to VHR: All. The total number of households, while positively associated with VHR: All ($r= .15$, $p<.05$) and STRs ($r= .10$, $p<.05$), is not as strongly correlated with rental property presence as one may expect.

Table 3.5. Correlations of all Chapter III Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Home Value									
(2) Median Household Income	.74**								
(3) VHRs: All	.08*	- .12**							
(4) VHRs: Entire	.14**	- .09**	.43**						
(5) VHRs: Room	- .05	- .26**	.40**	.69**					
(6) STRs	.08**	- .06	.86**	.26**	.21**				
(7) Concentrated Disadvantage	-.49**	-.47**	.03	-.11**	.05	-.02			
(8) Racial Heterogeneity	-.14**	-.27**	.23**	.21**	.25**	.07*	.21**		
(9) Residential Instability	-.36**	.08*	-.13**	-.12**	-.00	-.14**	.36**	.30**	
(10) Total Households	-.03	.07*	.15**	-.03	.02	.10**	.01	.11**	.19**

* p<.10, **p<.05

Multivariate regression models were analyzed first for each of the IVs with all DVs of interest and all VHR properties. Results are presented below in Table 3.6. Collinearity diagnostics indicated that STRs and all VHRs are collinear (VIF>4). Given this, STRs were excluded from Table 3.6.

Table 3.6. Negative Binomial Results with Aggregated VHR Properties

	Residential burglary		Substance crimes		Disturbances	
	IRR	Z	IRR	Z	IRR	Z
VHRs, Aggregated	0.99	-1.01	0.99	-2.00*	0.99	-2.52**
Conc. Disadvantage	1.46	5.85**	1.79	6.14**	1.82	7.14**
Residential instability	0.90	-0.37	1.69	1.34	0.94	-0.20
Racial heterogeneity	0.80	-0.75	0.77	-0.59	0.64	-1.40
Bars and nightclubs[33]			1.06	3.23**	1.05	3.17**
Spatial lag	1.00	12.44**	1.00	10.76**	1.00	10.02**
Likelihood ratio χ^2 (5)		217.51**		294.47**		213.93**
Pseudo R^2		0.07		0.13		0.04

*p < .05; **p < .01; IRR=incidence rate ratio. Constant term has been omitted from display. Households were used as an exposure variable for residential burglary, population for substance crimes and disturbances.

When VHR properties are analyzed in a listing-aggregated manner, VHRs are negatively and significantly associated with substance crimes (z= -2.00, p<.05) and disturbances (z= -2.52, p<.01), controlling for all other variables in the models. VHRs are negatively and not significantly associated (z= -.1.01, p>.05) with residential burglary.

[33] Bars and nightclubs were not included in the residential burglary models because of weaker theoretical support for their inclusion with that crime type compared to substance crimes and disturbances. However, when included in the models, they are a significant independent variable, though Airbnb variables do not change in direction or significance in the models.

Concentrated disadvantage is significantly and positively associated with substance crimes (z= 6.14, p<.01) and with disturbances (z= 7.14, p<.01). Bars and nightclubs are also significantly and positively associated with substance crimes (z= 3.23, p<.01) and disturbances (z= 3.17, p<.01). After considering the other variables, residential instability and racial heterogeneity are not significant in any of the three models.

The results from three negative binomial regression analyses using listing-disaggregated VHRs are presented in Table 3.7. The incidence rate ratios (IRR) are presented in the table. When VHR properties are disaggregated by listing type, the results are different from the *VHR: All* models. After controlling for other variables in the model, individual room VHRs were significantly and positively associated with residential burglary (z= 6.21, p<.01), substance crimes (z= 3.66, p<.01), and disturbances (z= 5.15, p<.01) while entire property VHRs were significantly and negatively associated with residential burglary (z= -2.88, p<.01), substance crimes (z= -5.49, p<.01), and disturbances (z= -6.75, p<.01). Concentrated disadvantage (z= 5.10, p<.01) and bars and nightclubs (z= 4.37, p<.01) both had a positive and significant relationship with substance crimes. Additionally, concentrated disadvantage (z= 6.19, p<.01) and bars and nightclubs (z= 4.30, p<.01) both had a positive and significant relationship with disturbances. Controlling for each other and all other variables in the model, residential instability, and racial heterogeneity were negatively and non-significantly associated with each of the three crime types. The short-term rental (STR) control variable was not significant in any of the models. The models without STRs were analogous to models with STRs.

Table 3.7. Negative Binomial Results with both types of VHRs

	Residential burglary		Substance crimes		Disturbances	
	IRR	Z	IRR	Z	IRR	Z
VHRs, Room	1.03	6.21**	1.02	3.66**	1.03	5.15**
VHRs, Structure	0.99	-2.88**	0.98	-5.49**	0.98	-6.75**
Short-term rentals	0.99	-0.86	0.99	-0.03	0.99	-0.39
Conc. Disadvantage	1.49	6.20**	1.61	5.10**	1.63	6.19**
Residential instability	0.73	-1.15	1.98	1.78	1.00	0.02
Racial heterogeneity	0.84	-0.59	0.72	-0.74	0.59	-1.70
Bars and nightclubs			1.09	4.37**	1.07	4.30**
Spatial lag	1.00	11.12**	1.00	10.66**	1.00	10.88**
Likelihood ratio χ^2 (5)		263.82**		323.61**		257.18**
Pseudo R^2		0.08		0.14		0.05

*p < .05; **p < .01; IRR=incidence rate ratio. Constant term has been omitted from display. Households were used as an exposure variable for residential burglary, population for substance crimes and disturbances.

Despite the significant results, the effects of vacation home rentals on crime were small. After controlling for the other variables in the models, every additional *individual room VHR* in a CBG corresponded to a 3% increase in residential burglary and disturbances, and 2% increase in substance crimes for an entire year among neighborhoods, many of which had low counts of crimes. Every additional *entire property VHR* corresponded to a 1% decrease in residential burglary, and a 2% decrease in substance crimes and disturbances in neighborhoods in 2018.

Discussion

This study found a substantial difference in results depending on property listing type more so than crime type. When all VHR properties were aggregated in models, there was a non-significant effect of properties in the residential burglary model, but significant and negative in substance crimes and disturbances models.[34] VHR properties in which an individual room was rented were positively associated with all types of crime in this study, and VHR properties in which the entire structure was rented were negatively associated with all types of crime in this study. These associations were all significant ($p<.01$). This was found to be the case after controlling for spatial crime concentration, the location of bars and nightclubs, social disorganization variables, and population. However, the models with total VHRs in which properties were not separated by listing type were significantly and negatively associated with substance crimes and disturbances. This highlights the importance of considering listing types of VHR properties (e.g., Van Holm & Monaghan, 2021; Xu et al., 2019).

There are several possible explanations. First, it could be that entire properties are more commonly operated by professional hosts (Arvanitidis et al., 2020) who manage the properties better, maintain facility quality, or are otherwise better at rapport building with prospective renters because they have better rental and marketing expertise (Gu et al., 2020). It could also be that individual room VHRs are more commonly operated by hosts who have negative interactions with guests (Binns & Kempf, 2021), or that when strangers live in close proximity on vacation, crimes are more likely due to conflict that may arise because of the use of shared spaces.

While Roth (2020) did not find a significant relationship between whole-unit properties and either acquisitive or disorder crimes, the associations were negative, like

[34] When an interaction of concentrated disadvantage on Airbnbs was investigated, it was observed that the significant and negative effect of Airbnbs in the disturbance model was the result of moderately disadvantaged neighborhoods (those in the third quartile of disadvantage). These models are presented in the Appendix. Future research should further consider neighborhood interactions in VHR research.

those reported here. This is similar to Lee et al. (2020) who found a negative, though non-significant, effect on crime in counties. Roth (2020), however, reported a significant positive association between private rooms and alcohol crime, which is consistent with the positive association detected in this study between individual room VHRs and substance crimes. The current findings are difficult to compare to those reported by Xu et al. (2019), who generally found positive significant relationships between VHRs and both violent and property crimes, though results varied from county to county. The findings are difficult to compare because Xu et al. (2019) analyzed aggregated measures of violent and property crime, used different kinds of statistical models, and analyzed a larger spatial unit of analysis.

There are multiple reasons why this study may have produced different results from previous work (e.g., Lee et al., 2020; Roth, 2021b; Xu et al., 2019). First, and as mentioned by Roth (2021b, p. 10), the difference in geographic aggregation may be an important factor. Smaller geographic units of analysis have been of central importance to crime science and geographic criminology for some time (Weisburd et al., 2009). By aggregating incidents to larger areas, there is an increased likelihood of missing the nuanced way concentrations occur in different shapes or of different sizes (Payne & Gallagher, 2016). For example, crimes may concentrate along a street or within a building on that street, but a county contains many streets, some of which will have an abundance of crime and some of which will not (Eck et al., 2005; Telep & Weisburd, 2018). Interpretation of results produced may be further complicated by issues, such as atomistic or collectivistic fallacies (Andresen, 2014; 2018; Lawton, 2018); a county may be dangerous in that it contains more crime than a nearby county, but each building, street, neighborhood, and city within the county is not uniformly dangerous.

A second methodological consideration is the incorporation of property management characteristics (Eck & Madensen, 2018; Payne, 2010; Rephann, 2009). Some of the ways that property managers may influence crime are via organizing the space, regulating conduct, controlling access, and acquiring beneficial resources (Eck & Madensen, 2018). While property management characteristics are often found to be important factors for guardianship of individual properties, consideration of such factors is complicated by the aggregated unit of analysis used in this study. Future studies using the individual property as the unit of analysis may be better suited to this task than studies that consider all properties in a neighborhood. Alternatively, multilevel modelling could be considered (Boessen & Hipp, 2015; Sampson et al., 1997). It is possible that variables accounting for collective efficacy (Sampson et al., 1997), such as neighborhood willingness to intervene on a neighbor's behalf, may have produced results different from what was found in this study (see also Jordan & Moore, 2018).

Another consideration is neighborhood awareness of VHR properties and underreported crime. This study did not account for the degree residents knew of local VHR properties. Awareness of VHRs may be important when considering guardianship and collaborative neighborhood response to issues posed by vacation rentals (Jordan & Moore, 2018; Xu et al., 2019). If neighborhood residents are aware of VHR properties, they may act through informal means to communicate disorder or nuisance issues at properties to the property manager or owner. This kind of direct communication may prevent law enforcement calls for service. Even disregarding social cohesion (Sampson & Groves, 1989), preventing VHRs from generating calls for service is in a neighborhood's interest as crime may negatively affect neighborhood property values (Ceccato & Wilhelmsson, 2011; Pope & Pope, 2012). This is also a possible explanation for the disparate findings.

Future research on vacation home rentals could also consider the buffer zone hypothesis (Bernasco & Dijke, 2020).[35] The buffer zone hypothesis is essentially that while a distance decay function exists in the journey to crime, with individuals being more likely to engage in crime close to home, there is also a buffer of some arguable distance around the home in which residents will not engage in offending because of the increased risk in being recognized (Brantingham & Brantingham, 1981). The geometric theory and crime pattern theory (Andresen, 2014) have both expanded on this notion, but it may be another consideration for these rental properties. It is possible that VHR occupants abstain from criminality within a buffer around the properties they are renting, and distance-to-crime research does not often differentiate property types, such as VHR properties (Bernasco & Dijke, 2020). Compared to long-term residents, it is also unclear what financial incentives VHR occupants have to not engage in crime, or whether the lack of familiarity with the areas around the rental property influences VHR occupants' awareness space of crime opportunities (Andresen, 2014). VHR properties may represent a difficult property type to understand in relation to the buffer zone hypothesis because data would need to distinguish property owner occupants from vacation occupants and how those two kinds of occupants interact with each other and adjacent buildings in the neighborhood (Binns & Kempf, 2021).

[35] This study was retracted in 2021 on the basis of non-replicable study selection and result concerns (see Bernasco & Van Dijke, 2021). It is still cited here, however, as it represents one of the most complete sources of information on various buffer zone hypothesis studies.

Importantly, this study reviewed the effect of all VHR properties alongside listing-disaggregated VHRs in a geographically smaller unit of analysis. This is unlike previous studies (e.g., Lee et al., 2021; Roth, 2021b; Xu et al., 2019). Previous research has found that owners who live closer to their rental properties may experience less crime (Rephann, 2009), and it is possible that when an owner continues to live in the property and only rents a room, instead of the entire structure, they provide greater guardianship. However, Roth (2021b) found that room-only rentals were positively associated with alcohol offenses, perhaps because younger individuals were more likely to rent only a room. It is also possible that the presence of the property owners during the rental process provides renters additional suitable targets to assault, burglarize, steal from, or manipulate (Felson & Eckert, 2018). Property owners being present may also increase detection (Jordan & Moore, 2018). However, in other criminology research, increasing detection and detectability may increase reported incidents, create a deterrent effect, or increase informal social controls that reduce reported incidents (Farrington & Welsh, 2002; Michael et al., 2012).

While this study acts upon the recommendation by Roth (2021b, p.11) to use a smaller unit of analysis, there are many ways future research may explore VHRs and crime. Given regulatory hurdles associated with VHR properties (Coles et al., 2017; DiNatale et al., 2018), future studies may benefit from comparing VHR properties to other forms of rental data, such as for hotels or motels. This study controlled for reported short term rentals (STRs); the STRs were not significant in any of the models and had little impact on other variables-as assessed with models including and excluding STRs.

Future research should also consider temporal disaggregation. It is a potential limitation of the current study and others on VHRs and crime (Roth, 2021b; Xu et al., 2019) that incidents and properties are aggregated temporally and use cross-sectional designs. The effect that VHR properties have on neighborhood crime may be short-lived, and longitudinal methods may be more appropriate (McDowall et al., 2019). Longitudinal methods may also address concerns about temporal order (for example, see Miller, 2000) and the notion that VHR owners select low-crime neighborhoods initially, regardless of whether VHRs subsequently affect neighborhood crime. However, longitudinal studies present their own issues, and concerns exist about the broad support for longitudinal research and discounting of cross-sectional studies (Cullen et al., 2019).

VHRs may not be continuously occupied and multiple renters may occupy the same dwelling over the course of a year. Understanding when the properties are occupied in relation to when crime is occurring would add temporal precision to VHR and crime associations. Understanding the proportion of the time that VHRs are vacant may be just as important (Roth, 2019). Lastly, there are property characteristics unique to VHRs and VHR users that may be useful to consider in future research. For example, review scores of properties and of renters (Chen & Chang, 2018) may provide insight into how well owners care for the properties and renter-owner relations. Lastly, this study examined crime and vacation home rentals in 2018, prior to the COVID pandemic. It is unclear how the pandemic could have affected several of the variables used in the present study. This study may not be generalizable to 2020, or years post-pandemic; it is currently unclear and should be considered further.

IV. STUDY TWO: RESULTS ACROSS VARIED SPATIAL UNITS

> If researchers intend to determine whether neighborhood effects matter, it is necessary to first observe that how neighborhoods are defined also matter.
>
> - Onubogu, 2013, p.63

Background

This chapter is the second to assess VHRs and crime in a spatial manner, but there are many possible directions that could be taken to achieve this. The approach used here partly relies on the suggestion of Lawton (2018, p.186) that "[ecological fallacies and the modifiable areal unit problem (MAUP)] can never be completely ignored, but can be limited through efforts…to examine results across different units of analysis." This study first re-examines VHRs and neighborhood crime in Austin, Texas in 2016 in census block groups. Then secondly, this study examines VHRs using ½ mile egohoods, a spatial unit of analysis with overlapping boundaries that attempts to minimize edge effects, analyze neighborhoods of equal size, and reduce the MAUP (Hipp & Boessen, 2013; Kim & Hipp, 2020).

This chapter, and hypothesis four regarding whether the results of Chapter III are found again using a different year of data, can be considered in terms of robustness. The interest is in the stability of the associations when measured with different units of analysis (such as CBGs and egohoods) and different years of data (such as 2016 and 2018). Robustness, and robustness tests, refer to a variety of things (for example, see Bradley, 1978; Clemens, 2017; Duncan et al., 2014; Kappenman & Keil, 2017). The interest in this chapter is to understand the resilience of the associations between VHRs and crime. There are many reasons why study results fail to be reproducible (e.g., Farrington et al., 2019; Laing et al., 2018); however, within geographic criminology the modifiable areal unit problem may be a central reason.

The modifiable areal unit problem (MAUP) is a problem with many names in the criminology and geographic literatures (Andresen, 2021; Gerell., 2017; Rengert & Lockwood, 2009).[36] It has been referred to in the context of unobserved heterogeneity (Andresen & Malleson, 2013; Worrall & Pratt, 2004), issues of spatial aggregation (Zhang et al., 2012), differences in macro spatial scales (Hipp et al., 2017), multiscale spatial problems (Quick, 2019), aggregation bias (Wooldredge, 2002), or a form of ecological fallacy (Oppenshaw, 1982). Broadly, this problem refers to how different results may be found depending on how individual things are aggregated (e.g., crime events, persons), to different spatial units of analysis with varying boundaries (Andresen, 2021; Onubogu, 2013). Perhaps the best everyday example of the MAUP is gerrymandering (Buzzelli, 2020); voting district boundaries may be arbitrarily drawn to produce multiple kinds of results with the same sample of voters.

MAUP is a problem that affects every discipline, has no certain solution, and can produce inconsistently misleading results (Buzzelli, 2020; Oppenshaw, 1982). It is a classic problem in spatial analysis (Bernasco & Elffers, 2010; Tita & Radil, 2010). This problem has been used, explicitly or implicitly, to justify the use of smaller units of analysis (Gerell, 2016; Oberwittler & Wikström, 2009; Payne & Gallagher, 2016).[37] It is possible that MAUP facilitates questionable research practices (Chin et al., 2021); researchers may produce the result that they want by altering the way individual

[36] See Onubogu (2013), Oppenshaw (1984), and Wilson (2013) for a more nuanced discussion including Simpson's paradox, zoning effects, and scale effects.
[37] More precisely, MAUP describes statistical smoothing that reduces numeric heterogeneity in larger spatial units (Buzzeli, 2020, p.172; Onubogu, 2013, p.13).

phenomena are aggregated. The only apparent solution to MAUP is transparency of discretionary decisions, and testing associations with units of varying size, scale, and orientation (Buzzelli, 2020; Lawton, 2018).[38] Egohoods present a unique case for MAUP concerns when incidents may influence multiple overlapping areas. While different spatial aggregations are an important consideration, so are the incidents being aggregated, and VHR research is lacking in this regard (e.g., Maldonado-Guzmán, 2020, p.12). Crime is known to concentrate and fluctuate at small spatial units of analysis (Hewitt, 2021; Payne & Gallagher, 2016; Weisburd et al., 2015), but support also exists to study crime in multilevel models, or in larger neighborhood contexts (Boessen & Hipp, 2015; Deryol & Payne, 2021; Sampson et al., 1997).

Recently, there has been an interest in measuring neighborhoods as overlapping areas, and there has been some support for this approach (Hipp & Boessen, 2013; Hipp & Bates, 2018; Kim & Hipp, 2020). One approach to considering neighborhoods as overlapping has been referred to as egohoods (Glas, Engbersen, & Snel, 2019; Hipp & Boessen, 2013; Zampatti, Ballarino, & Squazzoni, 2019) and relies on the notion that neighborhoods should be considered in terms of having "fuzzy boundaries," influence from adjacent areas, and theoretical explanation for neighborhood geographic span. Activities in one neighborhood may influence those nearby, barring any spatial irregularities and physical boundaries (such as rivers, highways or others, see Hipp & Boessen, 2013, p.297; Kim & Hipp, 2017) that partition the area from those nearby.

[38] While this is communicated as if associations should remain constant at every unit of analysis, research regularly finds this is not the case, and it may not be measurement issues. For example, poverty may affect individuals differently than how poverty affects neighborhoods of individuals (Patterson, 1991; Sharkey et al., 2016), and this is not necessarily a MAUP issue. Caution must be exercised when generalizing between units of analysis (Andresen, 2014).

Furthermore, these egohoods seem to account for crime and social disorganization relevant variables to a greater degree than census block groups and tracts (Hipp & Boessen, 2013, p.306-309). Egohoods may be constructed in a manner influenced by theory more than the population-determined census areas. For example, ½ mile buffers more closely resemble distances that persons may travel near their home (Nicotera, 2007; Wu et al., 2020), and it may reflect the mixing of persons based on their routine activities (Hipp & Boessen, 2013), and these travel distances may cross roads, city blocks, and other settings.

However, the non-overlapping boundary approach presents its own limitations, and it is a new direction for neighborhood research. One limitation with the egohood approach is that the necessary transformations are time-intensive and non-intuitive, unlike easily used census areas (Hipp & Boessen, 2013; Nicotera, 2007). A second limitation is that this approach also requires reliance on known and possibly faulty assumptions. For example, using larger spatial units of analysis to proportionately assign values to smaller subsumed units can be an atomistic fallacy (Andresen, 2014). The novelty of the approach also means that studies assessing MAUP issues have not yet tested egohoods in the same way that areal grids, planning districts, or census areas have been tested (see Onubogu, 2013). Despite these concerns, this approach has empirical support (e.g., Hipp & Boessen, 2013; Hipp & Bates, 2018; Kim & Hipp, 2020; Zampatti et al., 2019).

One issue with egohoods, and spatial units of analysis in general, concerns the size of the area to be used. Theoretically, little guidance is offered for appropriate operationalizations of concepts like “near”, “around”, or “close to” nodes, paths, crime generators, and so forth (Groff, 2011; Ratcliffe, 2011). Many concepts within the environmental criminology literature require decisions regarding the size of an area to study, and research has been slow to quantify appropriate distances for different concepts (Lawton, 2018; Rengert & Lockwood, 2009). For example, the buffer zone hypothesis asserts that individuals may not engage in crime immediately around their home (Bernasco & Van Dijke, 2020). Place-based crime prevention efforts may find that prevention initiatives influence areas more intensely closer to the intervention (Groff et al., 2004; Reinhard, Vàsquez & Payne, 2021). Criminogenic facilities, like liquor establishments, influence crime nearby the facility (Groff, 2011). An often-cited (e.g., Cozens et al., 2019; Rengert & Lockwood, 2009) law of geography is that closer things influence each other more than distant things (Tobler, 1970).

Regarding egohoods, there is not a uniformly accepted distance for establishing the distance thresholds (Hipp & Boessen, 2013). However, smaller distance thresholds may be better (Groff, 2011; Ratcliffe, 2011;2012). Egohoods tend to be operationalized as ¼ or ½ mile distances (Hipp & Boessen, 2013; Kim & Hipp, 2020), and crime associations with facilities are found within these distances as well, particularly with street network buffers instead of Euclidian distance buffers (Groff, 2011, pp.169-170). Because smaller distances are likely better, and because these thresholds present similarly sized egohoods as census block groups (albeit depending on population in CBGs, see Hipp & Boessen, 2013), this study will use ½ mile radial distances from origin points.

This study corresponds to hypotheses 4, 5, 6, and 7, which are:

H4: Model results for CBG analyses will be the same in study two, compared to study one, using data from 2016 instead of 2018.

H5: Vacation home rentals will be positively associated with residential burglary in egohoods.

H6: Vacation home rentals will be positively associated with substance crimes in egohoods.

H7. Vacation home rentals will be positively associated with disturbances in egohoods.

These hypotheses represent both confirmatory and exploratory analyses. Hypothesis 4 is confirmatory in its desire to assess the robustness of study one results using a different year of data. Hypotheses 5 to 7 explore VHRs and egohoods, with the assumption that the different spatial unit of analysis confirms what was found with the CBG analysis. The chapter also considers MAUP issues by using two separate spatial units of analysis.

However, using egohoods presents some limitations. For example, while studies have attempted egohoods of differing sizes (Hipp & Boessen, 2013), and originating from street segments (Kim & Hipp, 2020), blocks (Hipp & Bates, 2018) or individual's residences (Zampatti et al., 2019), there are consequences associated with sizing neighborhoods differently, and these egohoods differently, and the consequences have not yet been fully explored in the literature. These are topics of consideration for geographic criminology and the ecology of crime in general (e.g., Boessen & Hipp, 2015; Hipp et al., 2021; Kubrin et al., 2021; Kubrin & Weitzer, 2003; Smith, 2020). By creating smaller egohoods, for example, it is possible that portions of a city are not included in the analysis. Hipp and Boessen (2013, p.299) found that 2% of the egohoods with crime in their sample of cities were isolates; they had no spatial overlap and thus excluded some amount of area. This is because the origin of egohoods is a centroid, constructed this way so as to make egohoods of uniform spatial size. A block that is greater than the size of the egohood constructed from the block centroid will have parts of the block not covered by the egohood. If this larger block is adjacent to other blocks of similar size, no overlap exists. Because census areas are of variable size depending on population (e.g., see Hipp & Boessen, 2013; Sampson, 2011; Nicotera, 2007), egohoods account for phenomena differently as one progresses from the middle of the city outward. Street segments, depending on how segment is operationalized, will also be of varying size-influenced by urbanicity.

If smaller egohoods do not provide uniform and complete coverage of a city, a natural solution may be to begin at polygon boundaries instead of polygon centroids; however, this approach is flawed as well. In other words, if egohoods were constructed from the edges of a census block instead of the centroid of a census block, coverage of a city would be complete by design, but this presents another issue. Namely, that egohoods would no longer be of uniform size because block boundaries are not of uniform size. This presents observation comparison issues, and MAUP issues, which census areas also experience (Andresen, 2018; Lawton, 2018).

Figure 4.1 provides an illustration of these limitations.[39] In clockwise order, Figure 4.1. presents egohoods created with ¼ mile radii from census block centroids in the city center, ¼ mile radii from census block boundaries in the city center, ¼ mile radii from census block boundaries at the city periphery, and ¼ mile radii from census block centroids at the city periphery. Each of the images in Figure 4.1. presents nine Census blocks (colored green), nine block centroids (points in the middle of blocks), and nine ¼ mile buffers (blue) from block centroids or boundaries. While census blocks, or city blocks, are of more uniform size in the middle of the city, they become irregularly sized and shaped toward the boundaries of the city. The boundary created buffer in the city

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[39] Each of the four maps presented in Figure 4.1. are also presented full-page in the Appendix.

periphery (bottom right image) has a distance of 1.3 miles from the irregularly shaped block centroid to the furthest edge of the ¼ mile buffer created from the block boundary. [40]

Figure 4.1. Egohood Characteristics in City Center versus Periphery

[40] The “peripheral” bottom set of images of Figure 6.1. were selected randomly; more extreme examples are possible.

Lastly, like other operationalizations of neighborhoods, egohoods still cannot account for incomplete data on the outside of whatever boundary is established for the entire study area. For example, the studies in this dissertation examine the city of Austin, Texas. This is a city that is comprised of multiple counties, and this city has suburbs and outlaying regions that are policed by agencies that are not the Austin Police Department. Neighborhoods, whether they are overlapping or mutually exclusive, would be better understood in the context of more data, such as with additional data for the university campus and data from each of the sheriffs' offices belonging to adjacent counties. Egohoods address edge effects between observations (Egohood_1 to Egohood_2) by having overlapping boundaries within the territory, but cannot address edge effects on the boundary of the study area when data are not available. It is unknown whether boundary effects are uniquely problematic depending on neighborhood operationalization because spatial boundary research in criminology is lacking (Hipp & Williams, 2020; Kim & Hipp, 2018).

Methods

This study's two-fold objective is reflected in its methods. First, the study will replicate study one by using census block groups, social disorganization constructs, spatial lag variables, and count regression models using 2016 data. This provides greater confidence in the results of study one, and an assessment of whether the results appear stable using different years of data (Farrington et al., 2019; Laing et al., 2018). Secondly, this study will perform the same analyses using the egohood approach (Hipp & Boessen, 2013; Kim & Hipp, 2020) to assess whether using overlapping neighborhoods influence the results about vacation home rentals and crime. This provides greater confidence that the MAUP is of less concern for VHRs and crime variables using these methods (Andresen, 2021; Onubogu, 2013).

Data Sources[41]

Crime Data

Crime data from the Austin Police Department for 2016 were used for this study. The data are police incidents that generated a written report. Limitations for reported offenses and police data are present and recognized. Location and time data are available for each crime incident; location data were used to aggregate incidents to CBG and blocks for egohoods. Substance crimes data include incidents, such as underage possession of alcohol, distribution of alcohol to a minor, possession of drug paraphernalia, and possession of a dangerous drug. Disturbance data include disturbance incidents that are not "parental" or "family" disturbances; instead, disturbances relate to noise complaints, unlawful gatherings, and ordinance violations.

Crime data for Austin, Texas are publicly available and were downloaded for this study. While study one used data from the Austin Crime Viewer, study two has used data available through the Austin Open Data Portal. Data for 2016 were first separated based on crime type. Like study one, categories were then created for residential burglary, substance crimes, and disturbance incidents. The crime data from the Austin Open Data Portal contained more kinds of substance crimes than the Austin Crime Viewer, such as

[41] A variable was created for temporary accommodations (n=226) from 2016 parcel data in Austin, Texas. However, the variable was not a significant predictor, and the models presented in this chapter are the same with and without that variable present. Additional information about this can be found in the Appendix.

various marijuana possession crimes, resulting in a sample of approximately 6,300 incidents.[42] The residential burglary and disturbance incidents occur in approximately the same frequency in 2016 as they appeared in 2018 data. All crime incidents were geocoded into ArcGIS Pro using *DisplayXY Data* with a success rate of 100%; incidents were then aggregated to the spatial units used in this study.

Vacation Rental Properties.

In this study, VHR properties are represented by Airbnb properties. While many Airbnb properties are vacation home rentals, not all vacation home rentals are Airbnb properties. Other companies also facilitate marketing home rentals, including VRBO, or HomeAway, among others (Binns & Kempf, 2021; Jordan & Moore, 2018) and properties may be simultaneously listed on multiple platforms. Because of this, Airbnb properties should be considered a conservative estimate of the full scope of home rental properties (DiNatale et al., 2018). Data were obtained through AirDNA, a private company that documents Airbnb locations, and only properties active in 2016 were used in this chapter.

Bars and Nightclubs

The presence of bars and nightclubs has been previously associated with substance crimes and disturbance incidents (Twinam, 2017; Wheeler, 2019) and so were considered for this study. As noted in study one, liquor establishments may be one of the most studied facility types in environmental criminology (Cozens et al., 2019).

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[42] These two categories of substance crimes were significantly, positively, and highly correlated in census block groups (r=.96, p<.001), so the new classification was used for substance crimes due to the greater number of incidents.

Furthermore, bars may represent locations of interest for VHR occupants, and the availability of alcohol may influence those crimes (Cohen & Felson, 1979; Roth, 2021b). The Texas Alcoholic Beverage Commission (TABC) provides data on alcohol-related licenses, and permits issued in 2016 will be used for this study. The *Mixed Beverage Permit* type was used as it includes on-site sale and consumption of beer, wine, and spirits. After data were narrowed to the city of Austin, Texas, clipped to within the boundary, restricted to those created before 2017 and expired after 2016, there were 737 permit site locations used as a proxy for bar locations. Lastly, there was an initial geocoding success rate of 97% that increased to 100% after the first rematch process.

Socio-Demographic Variables

Similar to prior research (Mletzko et al., 2018; Roth, 2021b), data from the U.S. American Community Survey (ACS) were used to operationalize social disorganization in the study area. ACS 2016 five-year estimates will be used to assess the degree of concentrated disadvantage, residential instability, and racial heterogeneity in Austin, Texas. The concentrated disadvantage variable will be created by summing the standardized versions of the following items, and dividing the total by five: the percent of families below the poverty line, the percent of households receiving public assistance, the percent of unemployed residents age 16 and older, the percent of female householders, and the percent of residents ages 25 and older without a bachelor's degree (α =.63). Residential instability was calculated similarly after combining the percent of the population living in a different house compared to 12 months ago, and the percent of housing that is renter-occupied (α =.81). The racial heterogeneity variable will be created using Agresti and Agresti's (1978) index of qualitative variation, with the following racial groups being considered: White, Black, Asian, Native American and Alaska Native, and Other.

Analytic Strategy, CBGs

Social disorganization variables are constructed to measure concentrated disadvantage, residential instability, and racial heterogeneity (Mletzko et al., 2018; Roth, 2021b). Concentrated disadvantage and residential instability are both created as composite values using the formulas presented in Chapter III (Mletzko et al., 2018; Reinhard, 2021). Reliability analyses and confirmatory factor analysis were used to ensure that each aspect of the composite measure acceptably measures the same construct. Data for social disorganization variables, vacation home rentals, and crime were geolocated into CBGs in Austin, Texas, using ArcGIS Pro.

Concentration of crime were assessed using Nearest Neighbor analysis and Global Moran's I values in ArcGIS Pro. This was done in the same manner as in Chapter III and using the practices established for modelling spatial phenomenon for routine activity and social disorganization theories (e.g., Kubrin & Weitzer, 2003). These effectively establish whether crime incidents are concentrated and whether the incidents aggregated to the unit of analysis are spatially concentrated.

Table 4.1. Spatial Concentration Statistics

	Coef.	Z
Nearest neighbor ratio		
Residential burglary	.407	-66.98**
Substance crimes	.315	-104.39**
Disturbances	.270	-172.74**

CBGs, Global Moran's I		
Residential burglary	.270	22.21**
Substance crimes	.070	9.04**
Disturbances	.224	18.80**

(**) $p < .01$.

Count regression models were used to measure the degree to which VHRs, social disorganization variables, and spatial concentration account for crime in CBGs and egohoods in Austin, Texas. Stata was used to conduct this step of the quantitative analysis. The dispersion of data regarding their mean and variance, and the frequency of zero counts were used to establish which count model was most appropriate. Appropriateness is further accounted for with post estimation statistics for the AIC and BIC values between kinds of count models. Caution was taken to ensure that actual dispersion, instead of apparent dispersion, was present within the data (Hilbe, 2011). While several methods exist for distinguishing between actual and apparent dispersion, two used here include checks for multicollinearity using variance inflation factor (VIF) values, and for influential observations, such as via Cohen's d statistic.

Creation of Egohoods[43]

Egohoods for this study were created based on census blocks (Hipp & Boessen, 2013), instead of alternatives, such as street segments (Kim & Hipp, 2020), or residences (Zampatti et al., 2019).[44] Because population data were necessary at the block level, 2010

[43] Egohoods were constructed for this study using the following publications: Hipp & Boessen (2013, pp.299-304); Hipp & Bates (2018, pp.434-437); Kim & Hipp, (2020, pp.34-38), these are consistent with other publications (e.g., Barton et al., 2021; Glas et al., 2019; Hipp et al., 2021; Zampatti et al., 2019).
[44] This decision was informed by a lack of definitive research suggesting a preferrable unit, and due to data limitations.

decennial census block data were used. American Community Survey 2016 block groups were also used as these represent the most granular spatial unit in which social disorganization relevant variables are available for the creation of concentrated disadvantage and residential instability measures. The Austin Regulatory Boundary shapefile was used to clip the blocks and the block groups. After removing the correctional complex and city airport, there were 13,158 blocks and 602 block groups.

Social-disorganization relevant data were added to the blocks and the block groups. For racial/ethnic heterogeneity, five categories were used to be consistent with Chapter III. These categories include White, African American, Asian, Native American, and All Others. These population counts were at the block level. Five variables were used for social disorganization (Mletzko et al., 2018), as had occurred for the CBG analyses.

The two residential instability variables used include the percent of the population living in a different house compared to 12 months prior, and the percent of housing that is renter occupied. These seven variables at the census block group level were assigned to each block within each block group (Hipp & Boessen, 2013). With the assigned population, disadvantage, and instability variables in each block, block centroids were established using the *Feature to Point* tool in ArcGIS Pro.

Egohoods were established with the *Buffer* tool, with the origin of each ½ mile buffer being the block centroid of each block in the city (Hipp & Boessen, 2013). This resulted in 13,158 egohoods with ½ mile radius. The *Summarize Within* tool was then used to sum each of the population variables, and acquire the mean average of each of the seven disadvantage and instability variables for every block within each of the egohoods. Egohoods contained an average of 21.7 blocks, with a minimum of 1 block and a maximum of 69 blocks. Approximately 1.1% (n=144) of egohoods had no overlap (Hipp & Boessen, 2013, p.299). Each item of the five-variable scale for concentrated disadvantage was standardized, and the scale was created (α = .79) in egohoods. Each item of the two-variable scale for residential instability was standardized and created (α = .92) in egohoods. The racial heterogeneity variable was created using Agresti and Agresti's (1978) index of qualitative variation in the same manner as *Chapter III*, but with percentages of each race category corresponding to proportions among all blocks within each egohood, having used population data at the block level.

Figure 4.2 below provides an example of two overlapping egohoods created from adjacent census block centroids in Austin, Texas. It should be noted that this overlap produces observations likely more homogenous than mutually exclusive CBGs, because in egohoods, one incident may affect multiple observations. Large proportions of egohoods may overlap given the nearness of block centroids with small adjacent census blocks. However, as noted in the beginning of this chapter, the degree of overlap varies from the city center to the city periphery.

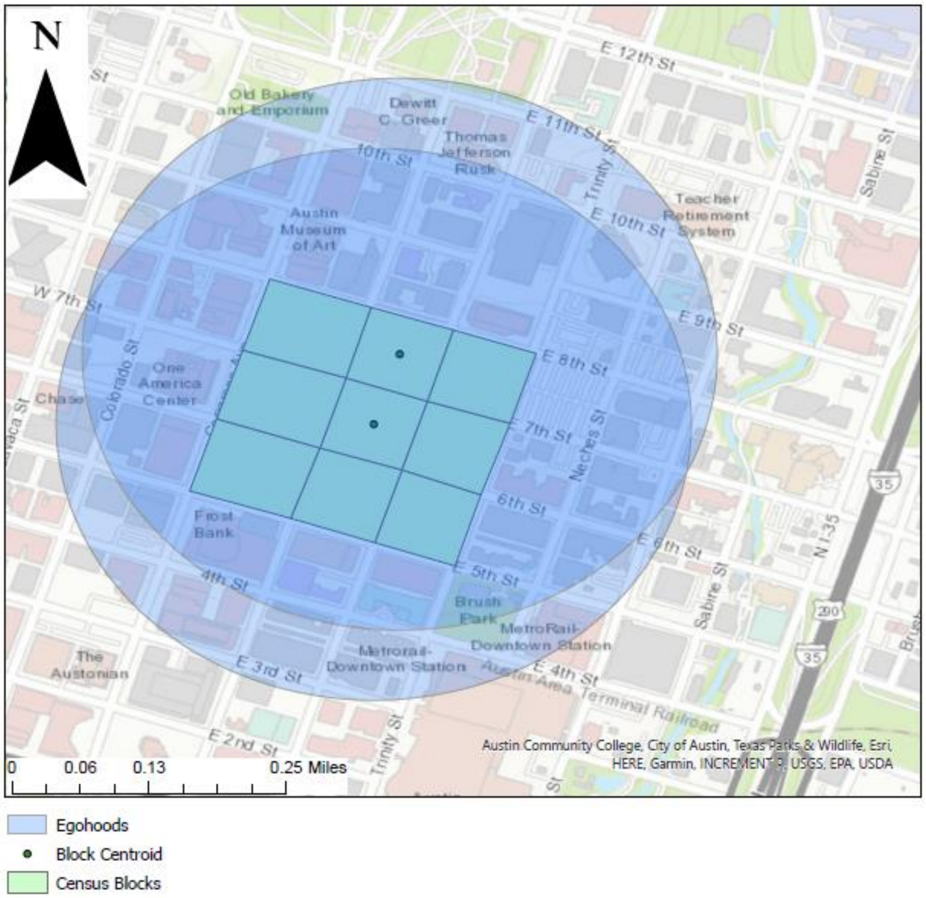

Figure 4.2. Egohood Example

Figure 4.3 provides a visualization of an illustrative example in which an egohood contains 69 census blocks-the maximum number among any of the egohoods created in this study. The blocks are of irregular shape; a creek is present and bisects some of the blocks. Additionally, blocks were assigned by the Census irregularly around Interstate 35. These blocks are within four numbered block groups, highlighted in blue in Figure 4.3. This provides an example of how one egohood may contain information uniquely compared to both blocks and block groups.

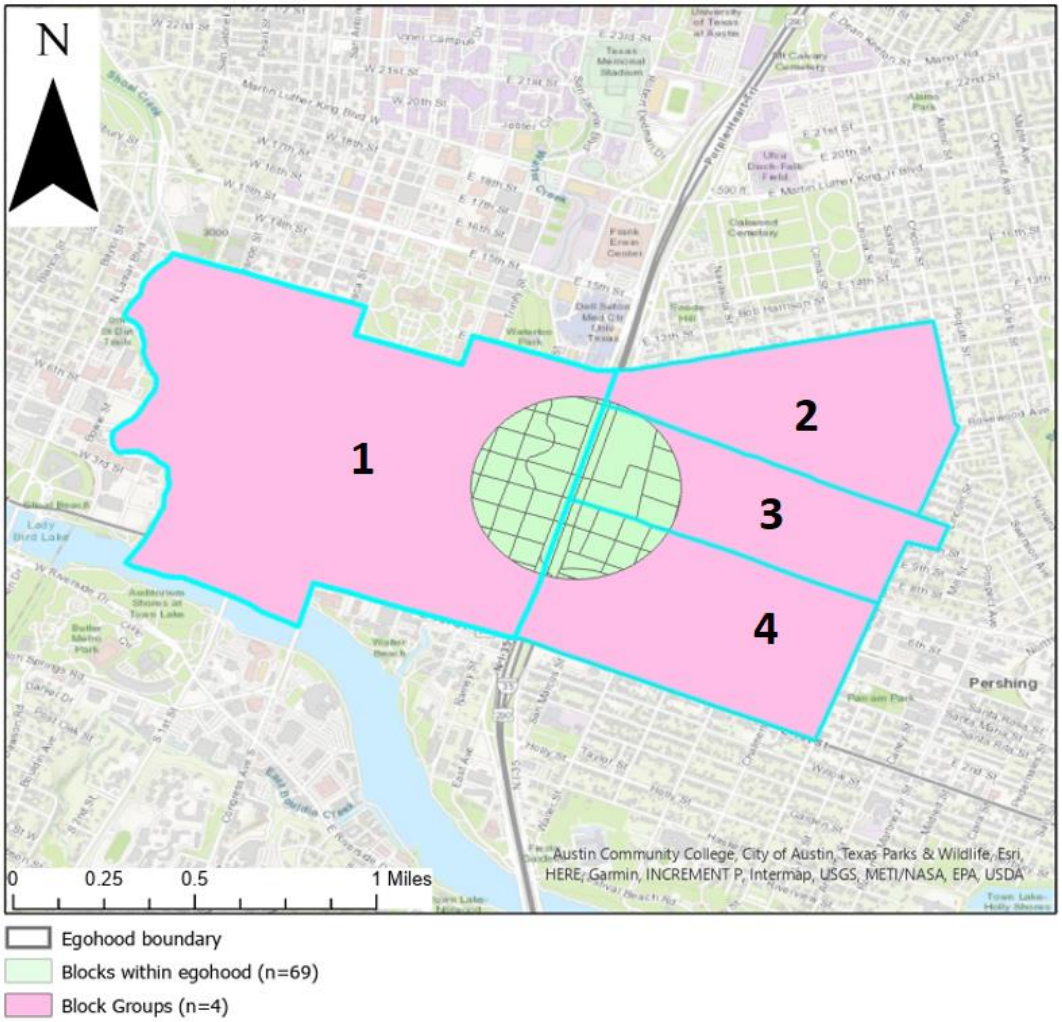

Figure 4.3. Egohood Example of Influential Observation

The last step was aggregating count variables of interest to egohoods and minimizing non-relevant columns in the datafile. Three kinds of crime incidents, bars, and three kinds of VHR properties for 2016 were added to egohoods. Because egohoods contain overlapping boundaries, incidents more clearly represent phenomena that influence multiple neighborhoods (egohoods) compared to incidents strictly influencing neighborhoods (blocks or block groups) in a mutually exclusive manner, when neighborhoods have non-overlapping boundaries. The final egohood dataset contained the seven aforementioned count variables, three social disorganization variables, and population. A non-zero logged population variable was also created and used as an exposure in models (Hipp and Boessen, 2013, p.301). The use of a spatial lag variable, or other approaches for correcting for spatial autocorrelation (Anselin, 2003; Anselin & Bera, 1998) was not attempted here because spatial error models have been found to closely approximate models without spatial error considerations when using an egohood approach (Hipp & Boessen, 2013, pp.310-311).

Results

The results for this chapter are presented first with descriptive results of the variables used, then with correlations for CBG variables and correlations for egohood variables. The descriptive results provide counts for CBG variables that were differently assigned to egohoods.[45] For example, the same 6,337 substance crimes that appear in mutually exclusive areas in the CBG analysis are the same substance crime incidents aggregated to overlapping neighborhoods for the egohood analysis. The same can be said of each of the other crime categories, bars, and VHR properties. Social disorganization variables are compared descriptively between the two spatial units of analysis. Spatial lag variables, used for the CBG analysis, are not presented descriptively because they represent a spatial error correction mechanism: mean values, sums, and counts provide no utility here.[46] However, correlations are likely different between CBG and egohood

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[45] The temporary accommodation variable had a non-significant effect in the CBG and egohood models, and was thus excluded from the results presented here. Future research should consider the number of available rooms in hotels, instead of the presence of hotels, when data allow.
[46] "Error-correction" here is used to describe the correction of known patterning of incidents which have spatially autocorrelated errors. I am not referring to ECMs in time-series analysis (e.g., Enders, 2015).

variables because of the shift to overlapping boundaries. After correlations, multivariate negative binomial regression models (NBREG) are presented with CBGs and with egohoods. NBREG models were selected after assessing model fit against Poisson models (Hilbe, 2011), and to be consistent with the results presented in Chapter III.

Descriptive Results and Correlations

Table 4.2 presents the variable summaries for the count used in this study. Overdispersion is present in the data, with greater variance than mean values for all variables. Uniformity is not present among overdispersed variables; bars experience a greater variance in relation to their mean compared to residential burglaries. In 2016, there were 15,173 total VHR properties, disaggregated into 10,339 entire structure rentals (68.1%), and 4,825 individual or shared room rentals (31.8%).

Table 4.2. Variable Summaries for 2016 (n=602 CBGs)

	Count	Mean	Median	SD	Min	Max
Residential burglaries	3,490	5.80	4	6.58	0	70
Substance crimes	6,337	10.53	4	30.79	0	680
Disturbances	15,284	25.39	14	31.87	0	421
VHRs (All)	15,173	25.20	11	40.89	0	504
VHRs (Structure)	10,339	17.17	6	33.63	0	448
VHRs (Room)	4,825	8.01	4.5	9.75	0	55
Bars	737	1.22	0	7.00	0	163

Social disorganization and population data are provided for CBGs (n=602) and for block-centered, ½-mile egohoods (n=13,158) in Table 4.3. Maximum and minimum values for each of the social disorganization variables were greater among egohoods, as was average racial heterogeneity and standard deviation values for both concentrated disadvantage and residential instability. The average population for CBGs was 1984 persons while the average value for egohoods was 860.

Table 4.3. Social Disorganization Variables and Populations across Units

	Mean	Median	SD	Min	Max
Census Block Groups (n=602)					
Conc. Disadvantage	0.00	-0.15	0.64	-0.92	3.07
Residential Instability	0.00	-0.17	0.92	-1.54	2.80
Racial Heterogeneity	0.33	0.33	0.17	0.00	0.72
Population	1984.33	1594	1390.64	16	10769
Egohoods (n=13,158)					
Conc. Disadvantage	0.00	-0.07	0.74	-1.54	4.45
Residential Instability	0.00	-0.03	0.96	-2.04	4.91
Racial Heterogeneity	0.43	0.44	0.14	0.00	0.74
Population	860.22	744	670.24	0.00	5589

Correlations are presented for the CBG variables in Table 4.3. All VHR properties are positively and strongly correlated with entire structure VHRs (r=98, p<.01) and with individual room VHRs (r=.80, p<.01). Bars are positively and strongly correlated with substance crimes (r=.90, p<.01) and with disturbances (r=.54, p<.01). The VHR variables are all strongly or moderately correlated with both substance crimes and disturbances.

The VHR: Room variable is more highly correlated with residential burglary (r=.35, p<.01) than either all VHRs (r=.16, p<.01) or entire structure VHRs (r=.09, p<.05).

Table 4.4. Correlations for CBG Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) VHR: All										
(2) VHR: Structure	.98									
(3) VHR: Room	.80	.68								
(4) Substance Crimes	.57	.59	.34							
(5) Disturbances	.32	.30	.33	.71						
(6) Residential Burglary	.16	.09	.35	.25	.66					
(7) Bars	.58	.62	.29	.90	.54	.06				
(8) Con. Disadvantage	-.11	-.15	.04	.09	.36	.32	-.07			
(9) Residential Instability	.30	.25	.38	.17	.31	.30	.12	.22		
(10) Racial Heterogeneity	-.15	-.18	.01	.09	.32	.31	-.02	.44	.28	
(11) Population	-.07	-.09	.03	.08	.25	.26	.07	.13	-.03	.22

Correlations are provided for the variables used in the egohood analyses in Table 4.5. The VHR variables are all less correlated with each other in the egohood analysis than in the CBG analysis, and the associations between VHR variables and crimes changed. For example, room VHRs have a substantially stronger correlation with disturbances ($r=.72$, $p<.01$) and residential burglary ($r=.71$, $p<.01$) than the other VHR variables do. However, like the CBG correlations, room VHRs still have the weakest correlation of the VHR variables with substance crimes ($r=.16$, $p<.01$). Bars are positively and strongly correlated with the VHR: All variable ($r=.98$, $p<.01$). Variance inflation factor values with each crime type as a dependent variable ($VIF>10$) provide further evidence that for egohood models, bars and VHR: All present a multicollinearity issue. Consequently, bars are not used as an explanatory variable in egohood models with the VHR: All variable.

Table 4.5. Correlations across Egohood Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) VHR: All										
(2) VHR: Structure	.70									
(3) VHR: Room	.37	.21								
(4) Substance Crimes	.25	.45	.16							
(5) Disturbances	.31	.29	.72	.60						
(6) Residential Burglary	.52	.22	.71	.05	.52					
(7) Bars	.98	.82	.35	.32	.33	.48				
(8) Con. Disadvantage	.19	.37	.13	.43	.37	.06	.25			
(9) Residential Instability	.48	.52	.25	.38	.37	.28	.52	.56		
(10) Racial Heterogeneity	-.05	.08	.07	.28	.26	-.01	-.02	.41	.19	
(11) Population	.44	.54	.25	.46	.41	.22	.49	.49	.58	.28

Multivariate Results

Negative binomial regression model results are presented comparing CBG and egohoods with the VHR and explanatory variables of interest.[47] Table 4.6 presents the residential burglary results with the VHR: All variable. The VHR: All variable is a positive and significant predictor of residential burglary in the CBG model (*b*=.00, p<.01), and in the egohood model (*b*=.02, p<.01), controlling for other variables in the models. While residential instability and racial heterogeneity are positively and significantly associated with residential burglary in both models, concentrated disadvantage is positively and significantly associated in the CBG model (*b*=.49, p<.01), but negatively and significantly associated in the egohood model (*b*= -.51, p<.01).

Table 4.6. All VHRs and Residential Burglary in CBGs and Egohoods

	Census Block Group		½ Mile Egohoods	
	Coeff [48]	Std Error	Coeff	Std Error
VHRs, All	.00**	.00	.02**	.00
SD: Conc. Disad.	.49**	.08	-.51**	.04
SD: Resid. Insta.	.23**	.05	.93**	.03
SD: Rac. Hetero.	.85**	.30	1.27**	.17
Bars and nightclubs				
Spatial lag	.00	.00		
Population	.00**	.00	.00	.00

[47] These models were assessed for fit against Poisson models. Egohood models were considered in multiple ways. When egohood models included the count of blocks within each egohood - as a method to account for incident overlap uniquely in the middle of the city versus the periphery-the VHR variables were still significantly associated with the crime variables and in the same directions as presented here without the block count variables. I also created models with logged population as an exposure variable (Hipp & Boessen, 2013, p.301), and they produced the same results for VHR and crime associations as those presented here.

[48] Coefficient values are presented to mirror the presentation of egohood research elsewhere (e.g., Hipp & Boessen, 2013). Due to the interest being in whether analyses are confirmatory for the CBG analyses, results are left in this form.

Likelihood ratio χ^2 (6,5)	166.17**	4629.61**
Pseudo R^2	.05	.16

Residential burglary models with VHR properties disaggregated by listing type are presented in Table 4.7. The VHR: Entire Structure variable was negatively but non-significantly associated with residential burglary in the CBG model, but negatively and significantly associated with residential burglary with the egohood model (*b*= -.02, p<.01), after considering all other variables in the models. Both models found the VHR: Room variable to be positively and significantly associated with residential burglary. The concentrated disadvantage variable was significant in both models, but positively associated in the CBG model (*b*=.46, p<.01), and negatively associated in the egohood model (*b*= -.42, p<.01). Lastly, bars and nightclubs were positively and significantly associated with residential burglary in the egohood model (*b*=.02, p<.01), but not in the CBG model.

Table 4.7. Disaggregated VHRs and Residential Burglary in CBGs and Egohoods

	Census Block Group		½ Mile Egohoods	
	Coeff	Std Error	Coeff	Std Error
VHRs, Entire	-.00	.00	-.02**	.00
VHRs, Room	.04**	.01	.01**	.00
SD: Conc. Disad.	.46**	.08	-.42**	.04
SD: Resid. Insta.	.19**	.05	.84**	.03
SD: Rac. Hetero.	.77**	.30	1.08**	.17
Bars and nightclubs	-.00	.00	.02**	.00
Spatial lag	.00	.00		
Population	.00**	.00	-.00*	.00
Likelihood ratio χ^2 (7,6)	197.14		4934.81**	

Pseudo R^2	.06	.17

The next set of models (presented in Table 4.8) provide the results for substance crimes as the dependent variable for CBG and egohood models. VHR: All was significant and positively associated in both the CBG model (*b*=.01, p<.01), and in the egohood model (*b*=.00, p<.01), after controlling for all other variables in the models. All three social disorganization variables were positively and significantly associated in both models. Bars had a positive but non-significant association with substance crimes in the CBG model.

Table 4.8. All VHRs and Substance Crimes in CBGs and Egohoods

	Census Block Group		½ Mile Egohoods	
	Coeff	Std Error	Coeff	Std Error
VHRs, All	.01**	.00	.00**	.00
SD: Conc. Disad.	.91**	.10	.42**	.02
SD: Resid. Insta.	.41**	.07	.30**	.02
SD: Rac. Hetero.	1.18**	.34	2.22**	.10
Bars and nightclubs	.04	.02		
Spatial lag	-.00	.00		
Population	-.00	.00	.00**	.00
Likelihood ratio χ^2 (5)	313.70		4960.06	
Pseudo R^2	.08		.08	

The disaggregated substance crime models are similar to the VHR: All models and are presented in Table 4.9. Entire VHR properties were positively associated with substance crimes, but non-significant in the CBG models, and significant in the egohood models (*b*=.04, p<.01). Room VHRs were positively and significantly associated with substance crimes in both models. The social disorganization variables were positive and significant in both sets of models. However, in the CBG model the population was negatively and significantly associated (*b*= -.00, p<.01), while bars (*b*=.06, p<.01) were positively and significantly associated after controlling for other variables in the models. In the egohood model, the opposite was true.

Table 4.9. Disaggregated VHRs and Substance Crimes in CBGs and Egohoods

	Census Block Group		½ Mile Egohoods	
	Coeff	Std Error	Coeff	Std Error
VHRs, Entire	.00	.00	.04**	.00
VHRs, Room	.04**	.01	.00**	.00
SD: Conc. Disad.	.88**	.10	.39**	.02
SD: Resid. Insta.	.38**	.07	.24**	.02
SD: Rac. Hetero.	1.15**	.33	2.07**	.10
Bars and nightclubs	.06**	.02	-.00**	.00
Spatial lag	.00	.00		
Population	-.00*	.00	.00**	.00
Likelihood ratio χ^2 (5)	335.18**		5304.76*	
Pseudo R^2	.09		.09	

The next set of models provide the results for disturbances in CBGs and egohoods. These results are presented in Table 4.10. VHR: All was significant and positively associated in both the CBG model (*b*=.00, p<.01), and in the egohood model (*b*=.00, p<.01), after controlling for all other variables in the models. All three social disorganization variables were also positively and significantly associated in both models. Bars had a positive but non-significant association with disturbances in the CBG model.

Table 4.10. All VHRs and Disturbances in CBGs and Egohoods

	Census Block Group		½ Mile Egohoods	
	Coeff	Std Error	Coeff	Std Error
VHRs, All	.00*	.00	.00**	.00
SD: Conc. Disad.	.80**	.09	.37**	.02
SD: Resid. Insta.	.41**	.06	.48**	.02
SD: Rac. Hetero.	.72**	.31	3.21**	.10
Bars and nightclubs	.02	.01		
Spatial lag	.00	.00		
Population	.00**	.00	.00**	.00
Likelihood ratio χ^2 (5)	247.87		5912.12	
Pseudo R^2	.05		.06	

The disaggregated disturbance crime models are presented in Table 4.11. Entire VHR properties were negatively and significantly associated with disturbances in the CBG model (*b*= -.01, p<.01), but positively and significantly associated in the egohood model (*b*=.04, p<.01). Room VHRs were positively and significantly associated with disturbances in the CBG model (*b*=.04, p<.01), and in the egohood model (*b*=.00, p<.01). The social disorganization variables were positive and significant in both sets of models. Bars were positively and significantly associated with disturbances in the CBG model (*b*=.04, p<.05), but negatively and significantly associated in the egohood model (*b*= -.00, p<.01).

Table 4.11. Disaggregated VHRs and Disturbances in CBGs and Egohoods

	Census Block Group		½ Mile Egohoods	
	Coeff	Std Error	Coeff	Std Error
VHRs, Entire	-.01**	.00	.04**	.00

VHRs, Room	.04**	.01	.00**	.00
SD: Conc. Disad.	.78**	.09	.39**	.02
SD: Resid. Insta.	.38**	.06	.24**	.02
SD: Rac. Hetero.	.64**	.30	2.07**	.10
Bars and nightclubs	.04*	.01	-.00**	.00
Spatial lag	.00	.00		
Population	.00*	.00	.00**	.00
Likelihood ratio χ^2 (5)	273.25		5304.76	
Pseudo R^2	.05		.09	

Discussion

These results only partially affirm this chapter's hypotheses. For example, hypothesis four, that CBG results would be consistent between 2016 and 2018, was variably affirmed, specifically for VHR: Room. Listing type appears to be an important consideration for whether results are consistent in CBG models. CBG results are provided comparing the two chapters in Table 4.13. VHR: All was positively and significantly associated with all crime types in 2016 but non-significant or significant and negatively associated with crime in 2018. Among all of the significant associations for VHR: Entire Structure, the results were consistently negative predictors of crime in both 2016 and 2018. Lastly, VHR: Room was significantly and positively associated with every crime type for both years of data. One explanation for the inconsistent results for VHR: All and VHR: Entire Structure is that the processes involved regarding crime and VHRs varied between these two years (Clemens, 2017; Farrington et al., 2019). Speculatively, VHRs were a newer phenomenon in 2016 compared to 2018, and it could be that VHR property management improved in 2018 after additional years of experience managing these properties. Or relatedly, that law enforcement improvements in the identification and response to these properties influenced the manners in which properties affected neighborhoods. Additionally, the political and legal climate of drug enforcement was in flux, both nationally, and in central Texas during this time (Menchaca, 2020; Plohetski, 2019). However, why that would affect VHR: All and not VHR: Room is unknown. One example is that these associations could be mediated by the degree of privacy afforded to renters who rent rooms versus entire structures.

Table 4.12. CBG results for each type of VHR property, Chapters III-IV

Property Type	Crime Type	2016 (Chapter IV)	2018 (Chapter III)
VHR: All	Substances	+	-
	Burglary	+	NS
	Disturbances	+	-
VHR: Entire Structure	Substances	NS	-
	Burglary	NS	-
	Disturbances	-	-
VHR: Room	Substances	+	+
	Burglary	+	+
	Disturbances	+	+

NS = not significant, p>.05

Regarding hypotheses five, six, and seven: among the 18 sets of results[49] for VHRs and crime, consistencies were observed in the significance and direction of the associations in 14 of the sets. Hypothesis five, regarding residential burglaries in

[49] VHR Variables (3) X Crime Types (3) X Spatial Units of Analysis (2).

egohoods, was not supported, though hypotheses six and seven were supported. This is presented in Table 4.12. Results could have been different between the two units of analysis for several reasons. First, aggregation of incidents to spatial units of different sizes (CBGs and egohoods) could have presented MAUP issues (Andresen, 2021; Onubogu, 2013). Second, the egohood design of incidents influencing multiple neighborhoods - uniquely from the center of the city to the periphery-could have produced varying results compared to mutually exclusive CBGs.[50] In other words, and as shown in Figure 4.1., egohoods and CBGs do not have the same spatial coverage of land area where crime may occur. Egohoods capture crime occurring in city centers, where census blocks are smaller, differently than they capture areas where census blocks are larger and no overlap occurs. By contrast, CBGs capture all areas because they are mutually exclusive, boundary connected regions. Third, the use of 2010 decennial Census population data being used, instead of the 2016 ACS five-year estimate data for CBG models could have produced different results. Fourth, the difference in sample size between units of analysis (CBGs, n=602; egohoods, n=13,158) could have influenced statistical power in a meaningful way. Relevantly, egohood models produced significant results for VHR: Entire Structure associations with substance crimes and residential burglary, unlike the CBG models.

Table 4.13. Result Comparisons for Chapter IV

VHR Type	**Crime Type**	**Results (CBGs)**	**Results (Egohoods)**
VHR: All	Substance Crimes	+	+

[50] When egohood models considered the number of egohood overlaps, VHRs were still significant and in the same direction as *traditionally* constructed egohoods. The non-traditional models attempted included the number of blocks in each egohood as an explanatory variable.

	Residential Burglary	+	+
	Disturbances	+	+
VHR: Entire Structure	Substance Crimes	NS	+
	Residential Burglary	NS	-
	Disturbances	-	+
VHR: Room	Substance Crimes	+	+
	Residential Burglary	+	+
	Disturbances	+	+

NS = not significant, p>.05

Specifically, VHRs were positively associated, in both aggregate and listing-disaggregated egohood models, for substance crimes and disturbances-hypotheses six and seven, respectively. In the listing-disaggregated egohood model, VHR: Structure was significantly and negatively associated with residential burglary; however, the VHR: All and VHR: Room variables were both positively and significantly associated. Hypothesis five, that VHRs would be positively associated with residential burglary, is partially supported but dependent on whether VHRs are considered in the aggregate or listing disaggregate.

The results of this study, that VHRs are (generally) positively associated with crime, is supportive of some past research (Binns & Kempf, 2021; Maldonado-Guzmán, 2020; Roth, 2021c). Similar to this study, Roth (2021c) found that VHRs were positively and significantly associated (p<.01) with larceny, simple assault, public drunkenness, and disorderly conduct in a sample of Texas cities (n=309). Maldonado-Guzmán (2020) found positive associations with VHR properties and property crimes, and with VHR properties to crimes against persons in Spain. They also found that individual room rentals had stronger crime associations than when entire properties were rented (Maldonado-Guzmán, 2020, p.11).

The differences found in results for CBGs in this chapter compared to Chapter III present support for future research to take a more nuanced longitudinal approach to VHR research. Specifically, if results vary despite the same approach being taken to understand VHRs and crime, with the same unit of analysis (CBGs), statistical method (negative binomial regression), study site (Austin, Texas), and by the same researcher, system instability issues or other concerns may exist about the robustness of VHR results (Bradley, 1978; Clemens, 2017; Farrington et al., 2019). It is unknown if the consistent positive association between crime and VHR: Room compared to Entire Structure suggests differences in the stability or evolution of property managers, tenants, or neighborhoods. This is an inquiry that future research should consider: how trustworthy cross-sectional results are for VHR and crime research. Current research assessing VHRs and crime are tend to be cross-sectional (Maldonado-Guzman, 2020; Roth, 2021b; 2021c; Xu et al., 2019), though research may benefit from assessing whether results are variable per year given multiple years of data.

This chapter has alluded to several limitations and many directions that future studies could take regarding egohoods. While initial research has assessed egohoods at varying distances from the same origin (Hipp & Boessen, 2013), MAUP-focused research could be considered that compares equal and unequal distances from multiple origins to establish the geographic and origin appropriateness for this design. Egohoods are of equal sizes, which corrects MAUP issues of unequal spatial boundaries. However, they are first based on inherently problematic areas: census data or street segments. An alternative approach could begin with grid areal units (e.g., Onubogu, 2013, p.43) and use centroids of those to capture the overlapping design. These studies would contribute to the VHR literature if rental properties were also used (Maldonado-Guzmán, 2020, p.12). A related concern is the unequal degree to which egohoods fail to provide coverage in less urban areas. For example, even if this approach is theoretically sensible, it may be more statistically appropriate in urban cities than in rural communities. Within this study, it was observed that the change in unit of analysis produced variably complete coverage of the entire city (CBGs cover an entire city, egohoods may not). Origin centroid distances could be a reasonable first step to guide whether the theoretical and statistical concerns are met for neighborhood boundary distances. For example, whether egohoods provide differing coverage in a meaningful way within one, three and five miles of a city center.

There are many potential future directions for VHRs and crime research based on these results. For example, Roth (2021b, p.50) notes that most studies do not control for tourism concerns. This study attempted to use a land use inventory with land parcel data that provided information about hotels, but these data did not contain information about occupancy, room availability, ambient population, and so forth. With only a count of temporary accommodations, models were the same as without the variable. If this study area were isolated by road, for example, cities in Hawaii or Alaska, data from Air Travel Consumer Reports could be used as a unique proxy for tourism as the reports provide monthly counts of flights and passengers (Department of Transportation, 2021). Proxies for tourism are often aggregated to larger spatial areas (e.g., Xu et al., 2019); overcoming this would help to disentangle rental properties from tourism or non-resident population generally.

V. STUDY THREE: VHRS AND TIME SERIES

> The philosophers are not constrained to look for operational definitions and can end up with asking questions of the ilk: 'If two people at separate pianos each strike the same key at the same time and I hear a note, which person caused the note that I hear?' The answer to such questions is, of course, 'Who cares?'
>
> - Granger (2001, p.50)

Background

The previous two studies have relied on cross-sectional designs to examine the association between crime and VHRs, through the lens of social disorganization and spatial analysis. Those studies relied on the criminological literature to satisfy the assumption of temporal precedence. A natural extension and verification of the previous two studies is whether variables $X_1 + X_2 + \ldots X_k$ are temporal predecessors to Y. In other words, are VHRs *causing* crime when time order is considered? Because of the recent emergence of vacation home rental platforms and the novelty of VHR and crime research, this is one of several uncertainties (Binns & Kempf, 2021; Ke et al., 2021). To date, most studies have only considered VHRs and crime using cross-sectional designs. Of note, Van Holm and Monaghan (2021) present incomplete panel data and cross-sectional designs, but the degree of missing monthly data somewhat undermines their research. Ke et al. (2021) and Han and Wang (2019) both use difference-in-difference methods in other locales.

The present study will briefly review concerns regarding temporal order as a criterion for causality (e.g., Cambell & Stanley, 1963, pp.64-65; Miller, 2000; Stafford &

Mears, 2015) before discussing time-series more broadly. However, data characteristics of a time series influence which analysis method is most appropriate, and inappropriate method selection produces different and spurious results (Ostrom, 1990; Shrestha & Bhatta, 2018). Due to this, and the necessity to first identify trend, drift, seasonality, structural breaks, and so forth, some literature on particular models is also presented in the *Results*, dependent on what is found with these data.

It should also be noted that while this study relies on data that are not cross-sectional, this still does not guarantee the observance of temporal cause and effect. For example, crime data may experience temporal error; crimes are reported when they are known about, but delays between when a crime occurred and when it is known about produces inaccuracies. A burglary on a vacant home may be reported sometime later once homeowners return and become aware of the crime (see e.g., Ratcliffe, 2002). Rental property data rely on assumptions that properties were rented when they were reported as being rented, though it is possible renting occurred without the use of a home-sharing company. There is no method to verify this, particularly years later with the data used in this study.

Within criminology, there are ongoing debates regarding temporal order - an important consideration for causal claims. Some argue for the utility of simpler kinds of measures and analysis (e.g., Lieberson, 1985). Some also assert that the increasing movement toward longitudinal data too quickly discounts cross-sectional designs (Cullen et al., 2019), which have been used by several criminologists to greatly influence the field (e.g., Hirschi, 1969; Gottfredson & Hirschi, 1990). However, a rebuttal in support of longitudinal studies may point to concerns regarding causality, specifically temporal order, as a reason to not rely too heavily on cross-sectional designs (Stafford & Mears, 2015). This study's interest in answering a research question with a temporal unit of analysis also prompts mentioning different criteria for causal claims. This is in part because different types of causality emphasize temporal measurement for understanding cause (e.g., Granger, 1969; Granger 2001).

Causality is the subject of extensive, and multidisciplinary scholarship (e.g., Granger, 2001; McCleary, McDowall, & Bartos, 2017, p.288; Pearl, 2000; Russo, 2009; Stafford & Mears, 2015). Many widely accepted definitions of causality have similarities. Definitions for causality often require the imposition of rules, assumptions, or axioms in the defining process. There are also many relevant limitations regarding any one definition of causality. For example, Granger (2001, p.54-55) asserts that it is possible that past evidence may be useless if causation changes from the past to the future; this possibility prompts the assumption that causality between entities remains constant in direction overtime, despite that not always occurring (e.g., system instability, Farrington et al., 2019). Definitions may begin with the assumption that cause precedes effect, but this has been the subject of debate as well (e.g., Bem, 2011; Francis, 2012; Salmon, 1990). It is for all of these reasons that a novel definition is not provided. The general definition for causality used by this study is similar to those used by others (Russo, 2009; Stafford & Mears, 2015, p.3); that is, "cause is essentially something which interferes with or intervenes in the course of events which would normally take place so as to change that course of events." This definition warrants additional nuance about *types* of causality and other issues.

There is an inherent uncertainty in causality, and it could be argued that establishing causality in the social sciences is an impossibility. First, researchers commonly do not know all of the causes of an effect ahead of time (Steel, 2012). This has been referred to as multiple things, such as an omitted variable bias (Stafford & Mears, 2015), which allows for the possibility that any statistically observable relationship is the product of unobserved or unknown variables; this topic also falls generally within concerns about model misspecification.[51] Within crime research specifically, faulty data are commonly used that experience some of these issues. For example, data from the Uniform Crime Report (UCR), National Incidence Based Reporting System (NIBRS), and police calls-for-service (CFS) are all police-reported data and are estimated to capture an inconsistent amount of all crime, depending on the type of crime, the location of crime, and the year of crime (e.g., Warner & Pierce, 1993). Data that are not from police sources, such as victim surveys from the National Crime Victim Survey (NCVS), also have known flaws (Lynch, 2006). This is partly why some scholars suggest that research should be about attempting to produce the best guess possible, not find an absolute truth (Farrington et al., 2019). Steel (2012), and others note that one of the main challenges for causality involves distinguishing between associated conditions and causal conditions. A great deal of potentially meaningful information cannot be discerned from correlated variables.

A second reason why establishing causality is difficult involves notions of probabilistic and deterministic causality (Granger, 2001). There are rarely definitive explanations for anything studied by social scientists. For example, there are no absolute theories of crime causation, there are a hundred theories that provide imperfect and

[51] See Shin & Sarkar (1997) for some of these concerns in time-series analysis

overlapping explanation (e.g., Akers et al., 2017; Cullen et al., 2018). The same explanations for crime have been known to experience changes in association intensity, significance, and direction depending on the unit of analysis (Patterson, 1991; Payne & Gallagher, 2016; Sharkey et al., 2016). In other words, there are differences in the degree to which a cause influences an effect generally and specifically. General discrepancies exist such that not all low socio-economic status (SES) individuals commit crime, and specific discrepancies exist when measuring low SES and crime in census block groups, versus census tracts, counties, or countries.

While no universally accepted definition exists, there are several generally accepted criteria used to help establish the presence of causality. For the purposes of this study, only three criteria for causality are briefly mentioned (i.e.: temporal precedence, non-spuriousness, empirical association) despite others existing (Pearl, 2000; Russo, 2009; Stafford & Mears, 2015). As already noted, exceptions to each of these may exist, though for the purposes of structuring and operationalizing causality, assumptions are used (Granger, 2001). The first is that cause(s) precedes effect (Marini & Singer, 1988; Miller, 2000). Inherent in this assertion is that it is known when causes occur and when effects occur, and they co-occur in a temporally successive manner. Study design and data limitations often prevent this. For example, cross-sectional designs measure cause and effect concurrently; then researchers use models that are asymmetric, and suggest theories for how their eventual interpretation is a possibility. In other words, this is an often-disregarded criteria for causality, despite it possibly being the most important (Miller, 2000). When time is used as a unit of analysis, “instantaneous” causality may be observed such that $Y_t = X_t$. This complicates establishing causal direction and detecting feedback effects, though this finding may be an artifact of data aggregation issues (Granger, 2001, p.59). A second criterion is that covariation is observed (Brandt, 2011). This is also phrased as the requirement that a non-zero correlation occurs between the cause and effect. A third criterion often used for establishing causality is that the relationship between cause and effect is not influenced by confounding or spurious variables (Pearl, 2000). However, it should be remembered that these are all criteria for establishing the theoretical notion of causality.

Econometrics generally instead makes the assertion that thousands of causes previously caused Y_t, and by using Y_{t-1}, it is less necessary to establish $X_1, X_2, \ldots X_k$. This may be viewed as undesirable by social scientists who instead choose to use the "disjunctive plurality of causes" to explain an effect (Marini & Singer, 1988, p.356). Granger causality, and many other methods using time-series, are interested in forecasting future values based on previous values, not on whether 20 facility types independently and jointly cause an effect (Cozens et al., 2019, pp.8-9). Time-series analysis may rely on univariate or bivariate associations, for example, when considering interrupted time series analysis (ITSA; McDowall, McCleary, & Bartos, 2019).

A time series is a collection of temporally successive observations of some phenomenon. It represents a useful approach for considering temporal precedence because it allows for analyzing associations between variables over time, and considers past values of the same variable (Ostrom, 1990; Pickup, 2015). Like other inferential statistics, time series is often first interested in using a sample of observations to generalize to the population, the population being time (Pickup, 2015; McCleary et al., 2017). The emphasis for time-series is on the data generating process, the associations between each observation in the sample and the amount of error between expected and observed values. Time series is econometric in origin, is often used to help differentiate correlation from causation, and has increasingly been used to analyze crime (Levitt & Miles, 2006).

Crime is often found to be seasonal in nature (Baumer & Wright, 1996; Farrell & Pease, 1994; Linning et al., 2017) and predictable on the basis of previous crime. Counts of crime reliably increase in an area during tourism seasons, or throughout the week based on previous high crime days that week and one week prior (Curiel, 2021; Johnson, Bowers, & Pease, 2012). For example, greater crime may occur on a Saturday if Friday experienced substantial crime, and/or the prior Saturday experienced substantial crime. Spatially, repeat victimization is more likely among targets close to previously victimized persons/places (Grove et al., 2012; Johnson & Bowers, 2013). Explanations for these spatial and temporal findings vary. Some of the most common explanations include risk heterogeneity and event dependence (Short et al., 2012), offender awareness and mobility patterns, or the target/victim being a crime attractor-a known opportunity for potential offenders (Brantingham, Brantingham, & Andresen, 2016).

In other words, past crime is a good explanatory variable for future crime, and this presents statistical issues (Pickup, 2015, pp.56-58; Ostrom, 1990, pp.14-16). Crime influencing crime, and crime being influenced by unmeasured variables, is the subject of extensive research in spatial econometrics (Anselin, 2003; Anselin & Bera, 1998). Spatial autocorrelation, considered in Chapters III and IV with spatial lag variables and spatial concentration statistics (Kubrin & Weitzer, 2003), is similar to temporal autocorrelation. For example, observations in July are more similar to June and August than other months of the year, and July observations are more similar to July observations in other years than would be due to chance (Baumer & Wright, 1996). These seasonal and non-independent observations can be addressed in time-series in a few manners, and one of them is with seasonal autoregressive integrated moving average[52] (ARIMA) modelling (Enders, 2015, p.96; McDowall et al., 2019, pp.43-44).

ARIMA modelling has several advantages over other forms of time-series analysis (e.g., Shrestha & Bhatta, 2018). First, it allows for identifying autoregressive (AR), integrated (I), and moving average (MA) components of a series occurring separately or collectively, and of different orders. Each of these three processes indicates that variable residuals are not serially independent; in other words, observations are influencing other observations in the same series. There is a "memory" such that one observation is influenced by past observations in some manner (McDowall, McCleary, & Bartos, 2019, p.22). AR processes have gradual decay of influence from past to future observations. For example, an $AR_{(1)}$ process indicates that Y_t influences Y_{t+1} greatest, more than how Y_t influences Y_{t+2}, and that influence is greater than how Y_t affects Y_{t+3}, and so forth. MA processes indicate the previous value's error term influences the present value (e.g., Y_t is dependent on ε_{t-1}), with little if any influence into future observations. Integrated (I) processes are non-stationary processes that are made stationary through differencing (Y_t - Y_{t-1}). Stationarity concerns whether the mean, variance, and autocorrelation of a series is stable or changes over time. Many long-run predictions require transforming a non-stationary series to be stationary. Non-stationary series cannot be generalized to the population; samples will all be irreconcilably different from one

[52] Semantically, ARIMA is written instead of ARMA (e.g., McDowall et al., 2019) to avoid confusion here, and because it reflects the software commands used (e.g., SARIMA, not SARMA).

another. Stationarity and other series' characteristics will be discussed further in the *Results* section with this study's data.

Lastly, higher order processes are possible and can be accounted for with ARIMA modeling. For example, an $I_{(2)}$ process indicates that the data are integrated, and the first-differenced data must be differenced again in order to achieve stationarity. However, higher-order processes are less common in fewer-observation time series, and the emphasis on parsimonious process detection further decreases the likelihood of using higher-order explanations (Enders, 2015, p.76; McCleary, McDowall, & Bartos, 2017, p.103).

Methods

An intrinsic aspect of referring to a study as using time-series methods is that the unit of analysis is temporal in nature. However, some studies that use time as a unit of analysis, or consider phenomena over time, do not use series as understood in this study. Other studies may instead rely on circular statistics (Hewitt et al., 2020), pre/post analysis, panel data (Van Holm & Monaghan, 2021), longitudinal data, or other kinds of analysis and methods. Because this study will use series of time, the research question is different than Chapters III and IV, despite all three studies being interested in crime and VHR properties. This change of question is reflected by hypotheses 8, 9, and 10, which all note that shift of unit of analysis from geographic to temporal. The research question for this study is:

1. Are VHR properties a significant predictor of crime rates over time?

This alters the variables being used for this study. For example, social disorganization variables are not used for this study as they are used for the other studies in this dissertation. This is because by controlling for previous crime (X_{t-1}), there is a control for the unmeasured independent variables that presumably influenced crime at X_{t-1} the same way that they influence crime at X_t. There is no reason to suspect that social disorganization did not influence crime last year but it suddenly does this year. Furthermore, a central aspect of social disorganization is its temporal stability (Kubrin & Weitzer, 2003), that regardless of the coming and going of neighborhood residents, crime occurs in certain neighborhoods over many years. Crime is often found to be stable in this manner in various geographic areas (Telep & Weisburd, 2018; Weisburd, 2015).

In order to assess whether VHRs are associated with crime while simultaneously considering seasonal and past causes of crime, temporal data are used. Monthly data from Austin, Texas, from November 2014 to December 2019 (n=61) are used with counts of vacation home rentals, disturbances, residential burglary, and substance crimes. The three crime variables are each aggregated from multiple crime types, in the same manner as for Chapters III and IV, and then rates are created using annual household estimates. Stata was used to conduct all time-series analysis for this study.

Data Sources

Crime Data

Crime data for Austin, Texas from 2014 to 2019 were obtained through the Austin Open Data Portal.[53] Three crime categories were considered and represent aggregated

[53] These years were selected to correspond to purchased VHR data and because they are pre-pandemic.

crime types as used in Chapters III and IV. Residential burglary includes residential structures and residential outbuildings. Substance crimes include incidents, such as underage possession of alcohol, distribution of alcohol to a minor, possession of drug paraphernalia, and possession of a dangerous drug. Disturbance data include disturbance incidents that are not "parental" or "family" disturbances; disturbances instead relate to noise complaints, unlawful gatherings, and ordinance violations. During this period there was a total of 15,208 counts of residential burglary, 31,356 substance crimes, and 23,817 disturbances.

Monthly crime rates were calculated using annual household estimates for three reasons. First, the emphasis on structures (VHRs) and likely on vacationers (persons not represented by local population estimates) prompted using buildings instead of city population estimates. Second, monthly estimates for the city for this time period are not available, either for population or households. Third, using some kind of rate is preferable to crime count data as both the population and number of households increased over this time period in Austin, Texas (Jankowski, 2021). The data used to create rates with the crime variables were obtained from annual American Community Survey five-year estimate data from 2014 to 2019.

Vacation Home Rental Properties

Similar to what was done in Chapters III and IV, VHR properties here are represented by Airbnb properties. The Airbnb properties should be considered a conservative estimate of the full scope of home rental properties (DiNatale et al., 2018), although they will likely be much more accurate than official local government records (Swiatecki, 2019). Data were obtained through a company that documents Airbnb locations, and only properties active from November 2014 to November 2019 were considered. The data are monthly and report unique property IDs for active VHRs each month during this period. However, properties are similarly reported if they are occupied or unoccupied each month, provided they are listed as active.[54] It is also possible that some actively listed properties are uniquely attractive to prospective VHR users in ways that this study cannot capture (e.g., professional hosts, Arvanitidis et al., 2020).

Analytic Strategy

A time-series design is used to assess the relationship between vacation home rentals and crime. However, there are many kinds of analysis that broadly fall within time-series analysis (Enders, 2015; Narayan & Smyth, 2004; Shrestha & Bhatta, 2018). This study begins with collinearity checks, tests of stationarity, tests for serial autocorrelation, and distributed lag models (DLM; Ostrom, 1990, p.58; Pickup, 2015, p.90), though if data are found unsuitable for DLM, alternative models will be considered. DLM models are regression models that may include lagged observations of dependent and independent variables, and they require that several assumptions be met (Pickup, 2015, pp.56-58; Ostrom, 1990, pp.14-16).[55]

Like the previous two chapters, the independent variables in this study are types of vacation home rental properties. The primary dependent variables are crime rates. However, time series data are commonly problematic for regression; time-series data may

[54] In other words, a limitation of the present study is that active properties may not have been occupied 100% during months they were active, though presumably, they were occupied greater than properties that were not actively listed and excluded from the present study.

[55] Several other kinds of models were considered for this chapter. Another kind of model considered was segmented regression, also known as piecewise regression (see Wagner et al., 2002). That approach was abandoned because these data were found to be seasonal, containing predictable change at set intervals.

be heteroskedastic, autocorrelated, and not normally distributed. Seasonality is also common among crime data, and seasonality is corrected in a finite number of ways (e.g., McDowall et al., 2019, pp.43-44). These conditions all ultimately determine which analysis will be used.

Limitations

The first potential limitation is regarding using crime throughout an entire city to understand vacation home rentals throughout an entire city. The decision to use entire cities or states for time-series analysis in criminology is not without precedent (e.g., Charles & Durlauf, 2013; Levitt & Miles, 2006). Environmental criminology typically favors micro spatial areas (Andresen & Linning, 2012; Lawton, 2018), such as street addresses (Payne & Gallagher, 2016) or street segments (Weisburd, 2015) because of what is known about crime concentration variability within larger geographic units of analysis, and the importance of closeness for measuring associations (Groff, 2011; Ratcliffe, 2011). Geographically near objects are more related than distant ones (Rengert & Lockwood, 2009). An intuitive approach may be to only consider crime within "neighborhoods" around vacation home rental properties. However, if neighborhoods are operationalized as 10-minute walking distances (Wu et al., 2020), ½ mile buffers (Hipp & Boessen, 2013), or census block groups (Nicotera, 2007) around each vacation home rental, crime occurring across the entire city would still be included. An alternative approach that could have been considered is panel data with both temporal and spatial components (e.g., Van Holm & Monaghan, 2021). That approach was not taken here for a few reasons, a principal one being that no study has used time-series analysis and considered seasonal crime issues with temporal data as this chapter does. It should also be noted that time-series analysis, particularly intervention analysis, can be applied to smaller geographic areas under other circumstances (Jones-Webb et al., 2021; Reinhard, Vasquez, & Payne, 2021).

This study, and most studies that rely on econometric approaches, are interested in forecasting more than whether any one explanation is a better predictor of the dependent variable.[56] The methods employed in this chapter instead assert that VHR variation contributes to predicting future crime more than previous crime alone. The more VHRs there are, the greater the exposure risk for experiencing crime associated with VHR properties.[57] Previous crime typically explains future crime (Curiel, 2021; Grove et al., 2012; Johnson & Bowers, 2013; Short et al., 2012), and causes of crime are often presented as temporally stable, such as low self-control, absent guardianship, and a host of structural variables (Akers et al., 2017; Cullen et al., 2018).[58] Lastly, methods to account for variables not directly tested are commonly used in econometrics (Marini & Singer, 1988), but also in spatial analyses when using spatial lag variables (Anselin, 2003; Anselin & Bera, 1998; Kubrin & Weitzer, 2003).

Results

Descriptive and Univariate

Each series was first inspected, numerically and visually, to understand whether

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[56] See Anselin (2003; 2010) for examples of geographic analyses that include spatial econometric considerations.

[57] See Chamlin & Sanders (2018) for a multivariate time series analysis that considers traffic incidents and traffic fatalities using a routine activity theory framework.

[58] See Weisburd et al. (2016) for a discussion on the temporal stability of social disorganization theory and crime concentration at place.

drift, trend, structural breaks, or other characteristics were present (Enders, 2015, pp.118-122). Trend would be identified if the series experienced mean values that appear highly dependent on time, either steadily increasing or decreasing across observations (Enders, 2015, p.181). Table 5.1 provides descriptive results of each potential independent variable and dependent variable. For each of the VHR variables, a substantial variation appears to be present given the range from minimum to maximum values. Figure 5.1 provides a line chart for each of the crime rate variables. The disturbance and residential burglary rates appear to be gradually decreasing, on average, from the beginning to the end of both series. The substance crime rate oscillates, with a visually distinctive surge in the middle of the series.

Table 5.1. Descriptive Statistics of Series

Variable	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**
Substance Crime	514	499	102	347	820
Disturbances	390	395	43	294	480
Residential Burglary	249	249	53	159	368
VHR, Structure	11453	15847	4653	3753	17687
VHR, Individual Room	4351	5108	1481	1285	5799
VHR, All	15847	16315	6101	5039	23167

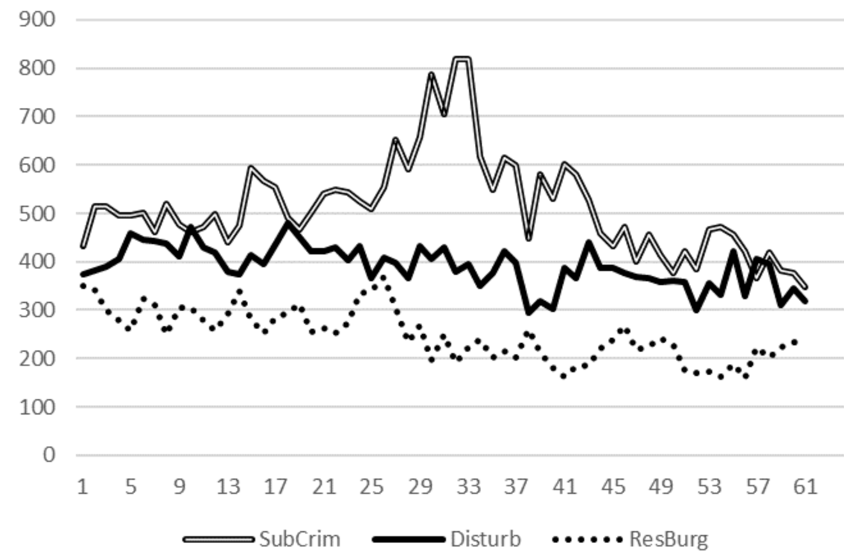

Figure 5.1. Crime Incidents per Month in Austin, 2014-2019 (n=61)

A line chart is presented below in Figure 5.2 indicating the count of vacation home rentals in Austin, Texas each month from 2014 to 2019. Confirming Table 5.1, each series fluctuates greatly from the lowest to the highest values. Trend appears to be present in both the VHR: All, and VHR: Entire Structure time series. The series are characterized as having stable but steadily increasing counts, month after month, from the beginning to the end of the samples. Additionally, these two series look correlated; fluctuations appear similar between the two series.

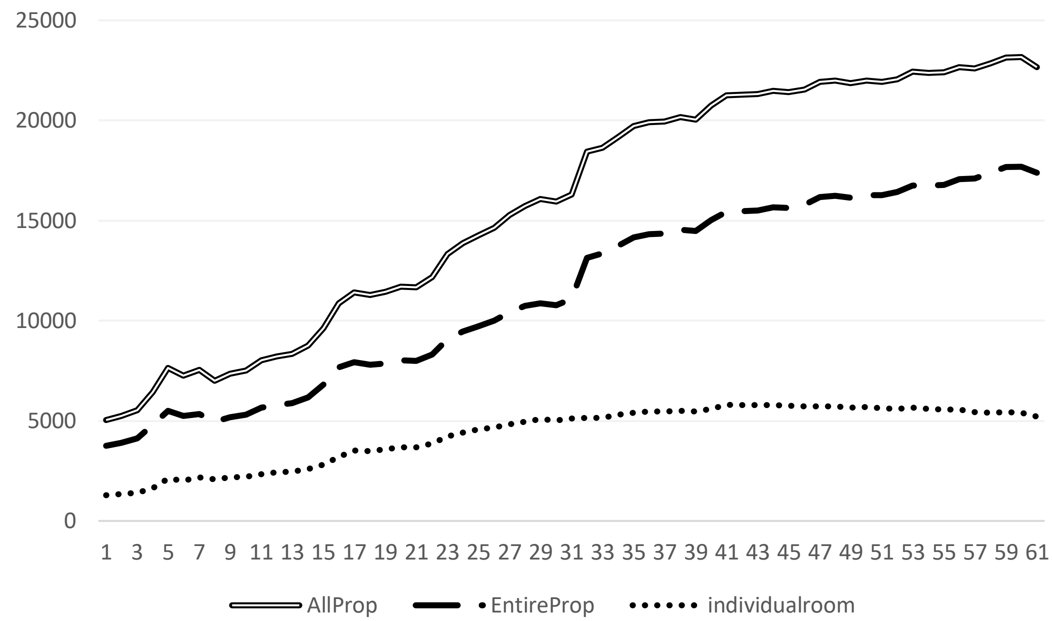

Figure 5.2. Vacation Home Rentals, in Austin Texas, from 2014-2019

Collinearity concerns exist for the listing disaggregated VHR properties. Table 5.2 provides correlations for each variable. Each of the VHR variables is highly correlated with each other. VHR: All is significantly, positively, and highly correlated with VHR: Structure ($r=.99$, $p<.01$), and with VHR: Individual Room ($r=.96$, $p<.01$). Crime variables are significantly and negatively correlated with each of the VHR variables. Crime variables are also significantly and positively correlated with each other. Post-hoc results from regression models find that multicollinearity is present for each of the VHR variables (VIF > 10). Given the explanatory overlap present for each of the VHR variables, only VHR: All will be considered in this study's time-series models. However, these correlations assume stationary data; non-stationary data experience greater estimation error that produces unreliable correlation coefficients (see Kristoufek, 2014; Schäfer, & Guhr, 2010).

	(1)	(2)	(3)	(4)	(5)
(1) VHR: All					
(2) VHR: Structure	.99				
(3) VHR: Room	.96	.94			
(4) Substance Crime	-.27	-.32	-.10		
(5) Disturbances	-.73	-.75	-.64	.37	
(6) Res. Burglary	-.80	-.81	-.75	.12	.60

Figure 5.3. Correlations of VHRs and Crime Variables

The next step for understanding each series, and ultimately deciding on the most appropriate modelling strategy, requires checking for stationarity, or the presence of a unit root (Pickup, 2015; Enders, 2015). Identification of a stationarity is important because this must be corrected to model the series' errors to be a white noise process that is integral for accurate long-run prediction (McDowall, McCleary, & Bartos, 2019, p.48). Figures V.1 and V.2 found series' characteristics potentially indicative of non-stationarity. Principally, the VHR: All series has a positive trend and the crime variables fluctuate uniquely, with the substance crime rate having a multi-month surge in the middle of the series. Because each test of stationarity and non-stationarity is conditional, multiple tests were conducted. This process is also complicated by considerations of fractional stationarity, and notions of stationarity as a non-dichotomous trait. Table 5.3 provides the results of five stationarity and unit root checks on each series.

Table 5.2. Results of all Univariate Stationarity Checks

Variable	**Correlogram/ Q Statistic**	**Lagged Coefficient Indicator**	**ADF**	**Phillips-Perron**	**KPSS**

VHR, All Properties	No	Close	Yes	No	No
Substance Crime	No	Yes	No	No	No
Disturbances	Close	Yes	Close	Yes	Yes
Res. Burglary	No	Yes	Close	No	Yes

As Table 5.3 indicates, there are inconsistent results for each series regarding whether the series is stationary or nonstationary. The correlogram and Q statistic, a portmanteau test to detect whether autocorrelations among a group of lags differ significantly from zero, found that each series' errors were significantly ($p<.05$) different from zero. Regressing the lagged variable as an indicator of the present variable ($Y_t=Y_{t-1}$) to assess AR bounds of stationarity and MA bounds of invertibility (McDowall, McCleary, Bartos, 2019, p.29) also indicated that variables were likely problematic. Coefficients were at or close enough to one to characterize the series as explosive in nature: the previous observations were significant predictors of future observations, and the series were not mean reverting. The Augmented Dickey-Fuller tests, Phillips-Perron tests, and KPSS tests similarly did not consistently find the series to be stationary.[59]

Due to the inconsistent results of these tests, the Box and Jenkins approach to autoregressive integrated moving average (ARIMA) modeling was selected (Box & Jenkins, 1970; Box & Tiao, 1975; Enders, 2015, p.76; McDowall, McCleary, & Bartos, 2019, pp.49-52). This approach is reasonable given the ARIMA modelling ability to distinguish between AR, I, and MA processes, and combinations thereof among the autocorrelations of univariate and multivariate associations of series. The ARIMA

[59] These tests are discussed in greater depth in Enders, 2015; McDowall et al., 2019; Ostrom, 1990; Pickup, 2015.

process also allows for considerations about seasonal processes, which is important given the demonstrated seasonality in many crime data (Baumer & Wright, 1996; Farrell & Pease, 1994; Linning et al., 2017).

The Box and Jenkins approach relies on identification, estimation, and diagnosis of series. This method is iterative by design (McDowall, McCleary, & Bartos, 2019, p.49). Identification may be done by assessing graphed autocorrelations and graphed partial autocorrelations to understand how each value *t* is associated with previous and future values (Y_{t-1}, Y_{t+1}). Identification of these associations allows for an understanding of whether models need to be corrected for the presence of autoregressive (AR), moving average (MA), or integrated (I) processes. While autocorrelations may produce visually distinct characteristics that suggest AR, MA, I, or seasonal ARIMA (SARIMA) components (Enders, 2015, pp.60-63), data generating processes may present higher-order components (e.g., $AR_{[2]}$; McDowall, McCleary, & Bartos, 2019, p.67), and combinations of these processes complicate adequate identification. The appropriately identified ARIMA model is distinguished as ARIMA($_{p,d,q}$) to differentiate AR, I, and MA components of specified order. For example, $ARIMA_{(1,1,0)}$ indicates a first-order autoregressive and integrated process.

Estimation occurs after the correct processes are believed to have been identified in the ARIMA($_{p,d,q}$) model. The ARIMA model is conducted with the processes adequately accounted for to produce errors that mirror a white noise process. Diagnosis then involves confirmation that the identification and estimation steps occurred correctly. Diagnosis often begins with a visual assessment of the autocorrelations of the series, followed by an assessment of the portmanteau Q statistic, and then the coefficient model values and probability results. The model is deemed adequate if the Q statistic results are non-significant ($p>.05$), ARIMA coefficient values do not exceed one, indicating the series is not explosive or outside of the bounds of invertibility (Enders, 2015, pp.77-78; McDowall, McCleary, & Bartos, 2019, p.29), and each included ARIMA component is statistically significant ($p<.05$). This indicates that the identification and estimation of the model were correct, and the data-generating process of the series is understood.

Univariate ARIMA modeling was first conducted for VHR: All and each of the crime variables. Using identification, estimation, and diagnosis, a suspected ARIMA configuration is selected, and the model is estimated. The estimated model is then diagnosed to determine whether the estimated model possesses a white-noise process. Figure 5.4 provides the graphed autocorrelations of VHR: All. The Box-Ljung Q statistic indicated autocorrelated errors ($Df_{[12]}$, $Q=449.04$, $p<.01$).

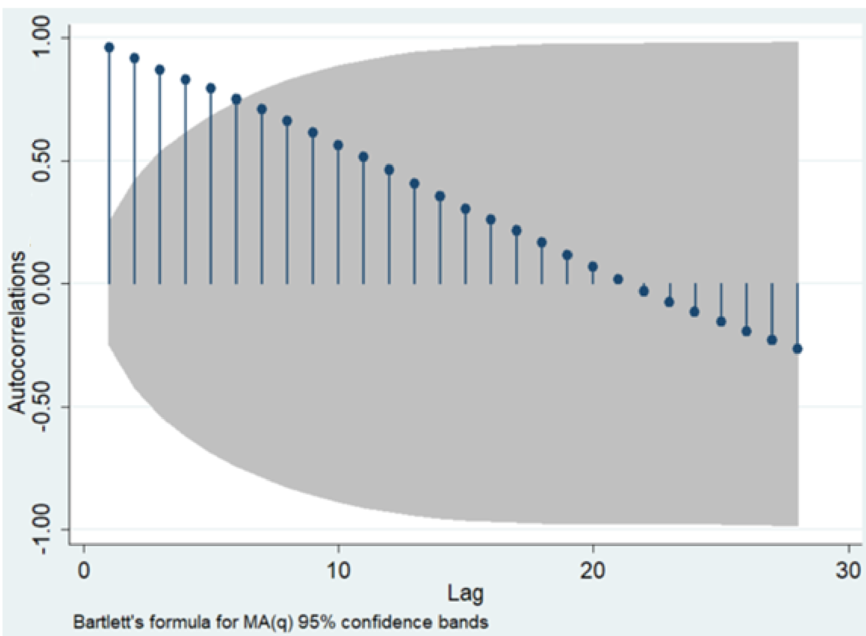

Figure 5.4. Graphed Autocorrelations of VHR: All

Figure 5.4 suggests that the series is $I_{(1)}$. Given this, the series was estimated in an $ARIMA_{(0,1,0)}$ model, and the univariate results are provided below in Table 5.3. The differenced variable (VHR: $All_{[D]}$) is a significant predictor of VHR: All, and Figure 5.5 presents the graphed autocorrelations. The figure and Q statistic, presented in Table 5.3 both indicate that the series is adequately explained as a first-order integrated series. Differencing appears to have adequately removed the serially correlated error (Chamlin & Sanders, 2018, pp.326-327; Enders, 2015, p.189).

Table 5.3. ARIMA(0,1,0) of VHR: All (n=60)

Variable	Coefficient	OPG Std. Error	Z
Constant	293.7	68.390	4.29*
/sigma	428.407	27.099	15.81*
Box-Ljung Q = 12.48, 12 df, p=.41			

* p<.01

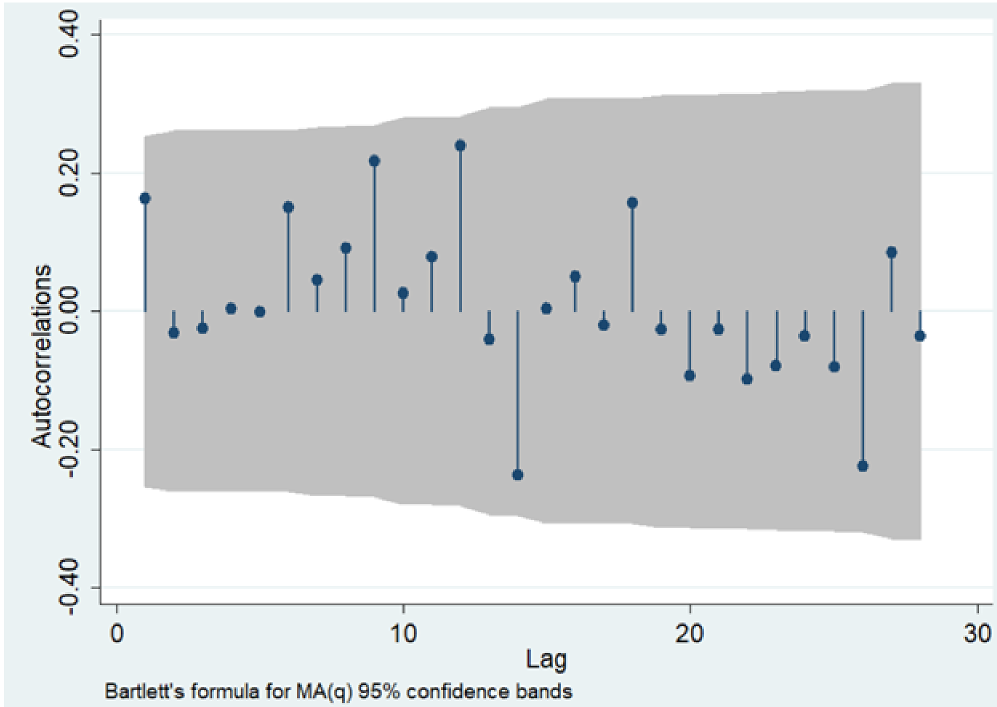

Figure 5.5. Graphed Autocorrelations of VHR: All(0,1,0)

Having adequately identified, estimated, and diagnosed the VHR variable, the crime variables are now each analyzed using the same Box and Jenkins ARIMA$_{(p,d,q)}$ methodology (Box and Jenkins, 1976; Enders, 2015, p.76). The substance crime rate series required eight iterations of the identification, estimation, and diagnosis process. For example, a seasonal ARIMA (SARIMA) model was estimated with ARIMA$_{(1,0,0)}$ SARIMA$_{(1,0,0,12)}$, but the SARIMA component was found not significant ($p>.05$). Figure 5.6 presents the initial graphed autocorrelations for the series. The graphed autocorrelations are difficult to interpret because the series is not oscillating in a MA$_{(1)}$ characteristic manner, or decaying to 0 in a manner consistent with AR$_{(1)}$ processes (e.g., Pickup, 2015, pp.115-139). Ultimately, the series are not adequately identified with any first-order processes. The Box-Ljung Q statistic indicated autocorrelated errors ($Df_{[12]}$, Q=171.02, p<.01).

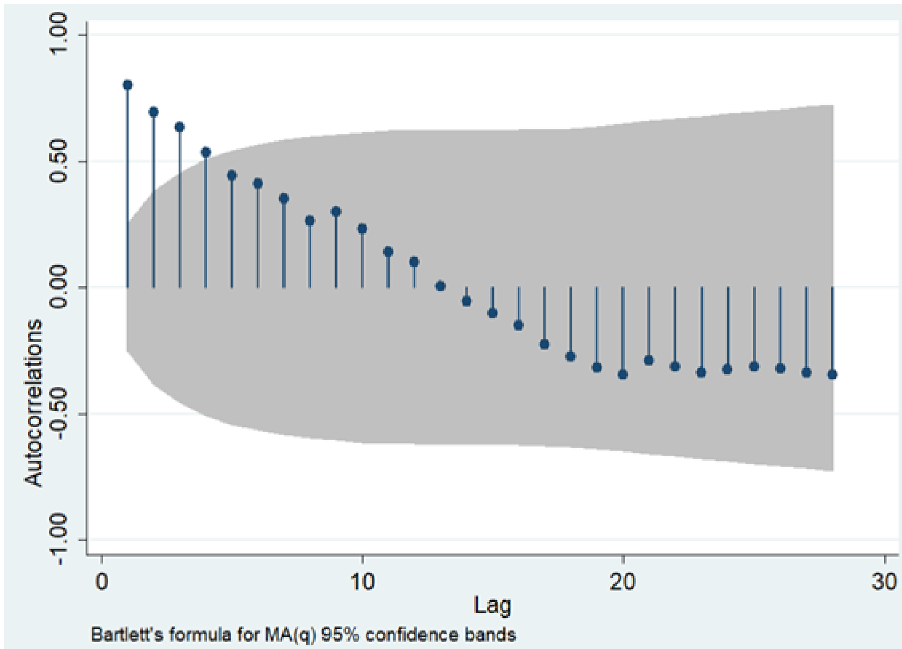

Figure 5.6. Graphed Autocorrelations of Substance Crime Rate

Among the eight iterations attempted, the best model fit for the univariate substance crime rate series is $ARIMA_{(2,0,0)}$. Table 5.4 presents the results of this model and Figures V.7 presents the autocorrelations of the residuals of this model. The constant is significant, and both $AR_{(1)}$ and $AR_{(2)}$ variables present coefficients <1. However, the $AR_{(2)}$ variable is not significant in the model (p>.05). Despite this, the Q statistic is adaquate (p>.05), and removing the $AR_{(2)}$ process renders the entire model inadaquate (Q statistic, p<.05). The difficulties associated with accounting for the data generating process of this series may stem from the surge substance rate in the middle of the series. Theoretical reasons to account for this are provided in the *Discussion.*

Table 5.4. ARIMA(2,0,0) of Substance Crime Rate

Variable	Coefficient	OPG Std. Error	Z
Constant	118.477	17.230	6.88*
AR(1)	.716	.120	5.94*
AR(2)	.147	.117	1.26
/sigma	14.084	1.174	12.00
Wald χ^2 (2) = 203.48*			
Box-Ljung Q = 19.07, 12 df, p=.09			

* p < .01

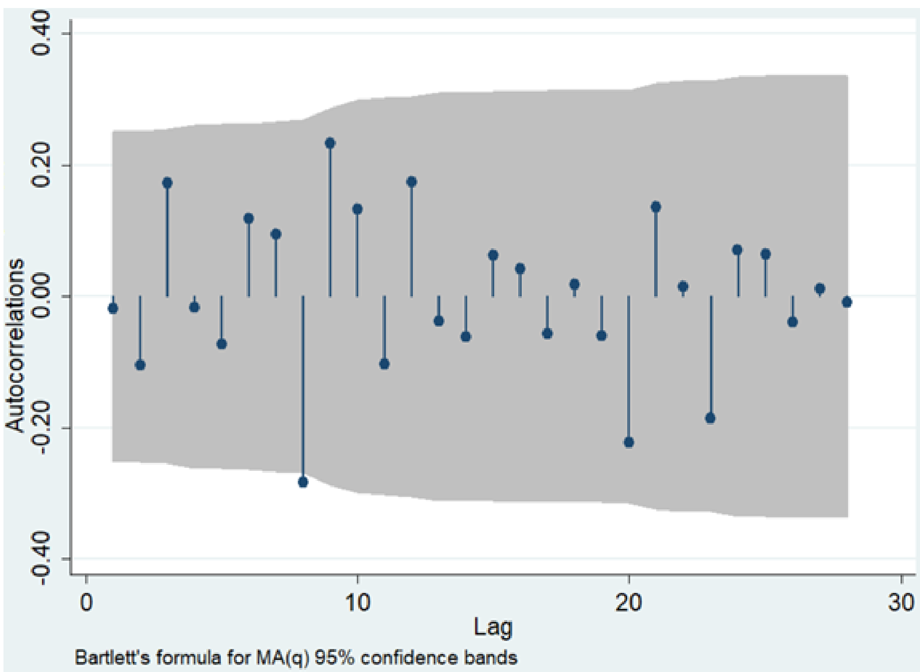

Figure 5.7. Graphed Autocorrelations of Substance Crime Rate(2,0,0)

The disturbances crime rate series required seven iterations of the identification, estimation, and diagnosis process. Figure 5.8 presents the initial graphed autocorrelations for the series. The graphed autocorrelations are somewhat consistent with an AR process, and also influenced by a seasonal component. A spike is observable at the 12th autocorrelation of the series in Figure 5.8; and given prior literature on seasonal crime considerations, a 12-month component was considered in the model. The Box-Ljung Q statistic indicated autocorrelated errors ($Df_{[12]}$, Q=162.36, p<.01).

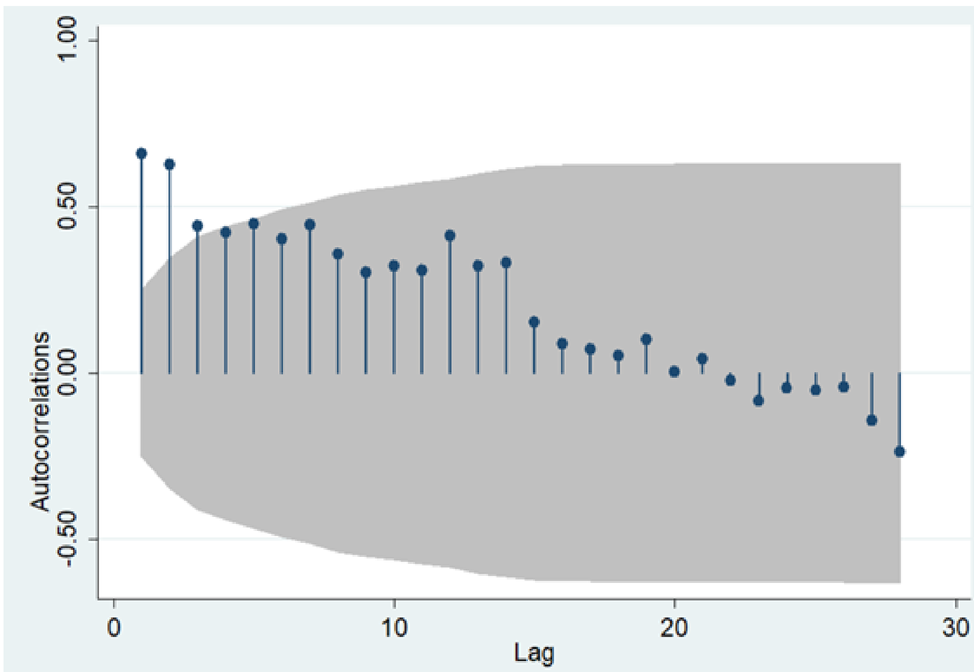

Figure 5.8. Graphed Autocorrelations of Disturbance Crime Rate

Among the eight iterations attempted, the best model fit for the univariate disturbance crime rate series is $ARIMA_{(1,0,0)}$ $SARIMA_{(1,0,0,12)}$. Table 5.5 presents the results of this model and Figure 5.9 presents the graphed residuals of this model. The constant is significant, and both $AR_{(1)}$ $SARIMA_{(12)}$ variables present coefficients <1. Additionally, both variables are significant (p<.05). The Q statistics are adaquate (p>.05), and the model appears to correctly account for the errors as a white noise process.

Table 5.5. ARIMA(1,0,0) SARIMA(1,0,0,12) of Disturbance Rate

Variable	Coefficient	OPG Std. Error	Z
Constant	93.252	5.384	17.32*
$AR_{(1)}$	.621	.146	4.25*
$SARIMA_{(1,0,0,12)}$	.478	.137	3.50*
/sigma	8.294	.634	13.07*

Wald χ^2 (2) = 41.39*
Box-Ljung Q = 11.27, 12 df, p=.51

* p < .01

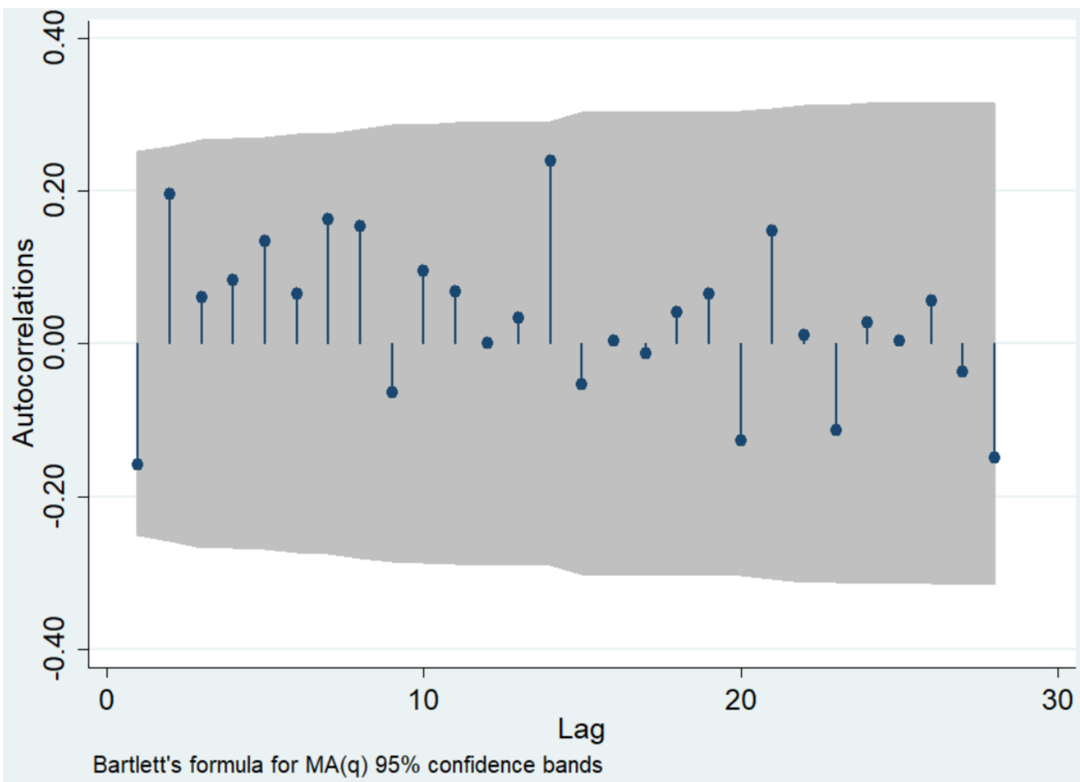

Figure 5.9. Graphed Autocorrelations of Disturbance Rate(1,0,0) (1,0,0,12)

The residential burglary rate series required eight iterations of the identification, estimation, and diagnosis process. Figure 5.10 presents the initial graphed autocorrelations for the series. The graphed autocorrelations are somewhat consistent with an AR process, and also influenced by a seasonal component. A spike is observable at the 12th autocorrelation of the series in Figure 5.10. Given prior literature on seasonal crime considerations, a 12-month component was considered in the model. The Box-Ljung Q statistic indicated autocorrelated errors ($Df_{[12]}$, Q=198.19, p<.01).

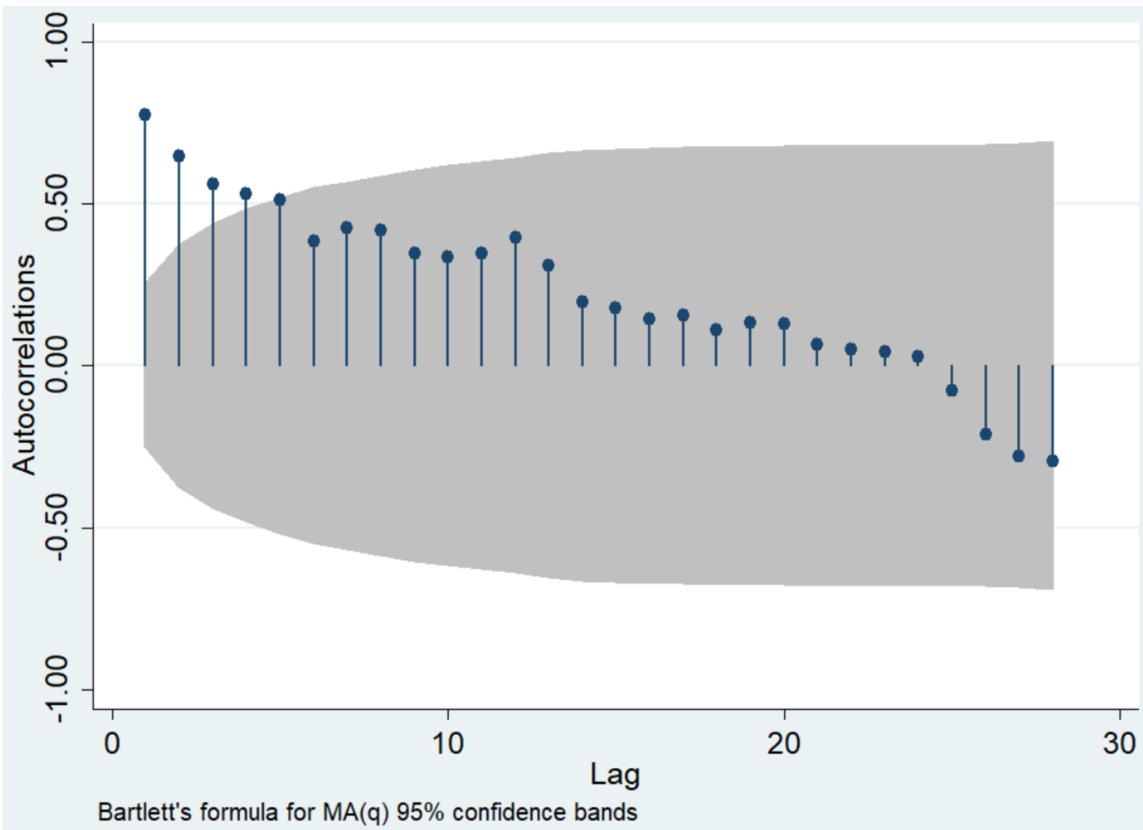

Figure 5.10. Graphed Autocorrelations of Residential Burglary Rate

Among the eight iterations attempted, the best model fit for the univariate residential burglary rate series is $ARIMA_{(1,0,0)}$ $SARIMA_{(1,0,0,12)}$. Table 5.6 presents the results of this model, and Figure 5.11 presents the autocorrelations of the residuals of this model. The constant is significant, and both $AR_{(1)}$ and $SARIMA_{(12)}$ variables present coefficients <1. Additionally, both variables are significant ($p<.05$). The Q statistics are adaquate ($p>.05$), and the model appears to correctly account for the errors as a white noise process.

Table 5.6. ARIMA(1,0,0) SARIMA(1,0,0,12) of Residential Burglary Rate

Variable	Coefficient	OPG Std. Error	Z
Constant	61.528	5.853	10.51*
$AR_{(1)}$	.789	.087	9.09*
$SARIMA_{(1,0,0,12)}$	.396	.139	2.84*
/sigma	7.954	.926	8.59*
Wald χ^2 (2) = 93.79*			
Box-Ljung Q = 9.05, 12 df, p=.70			

* p < .01

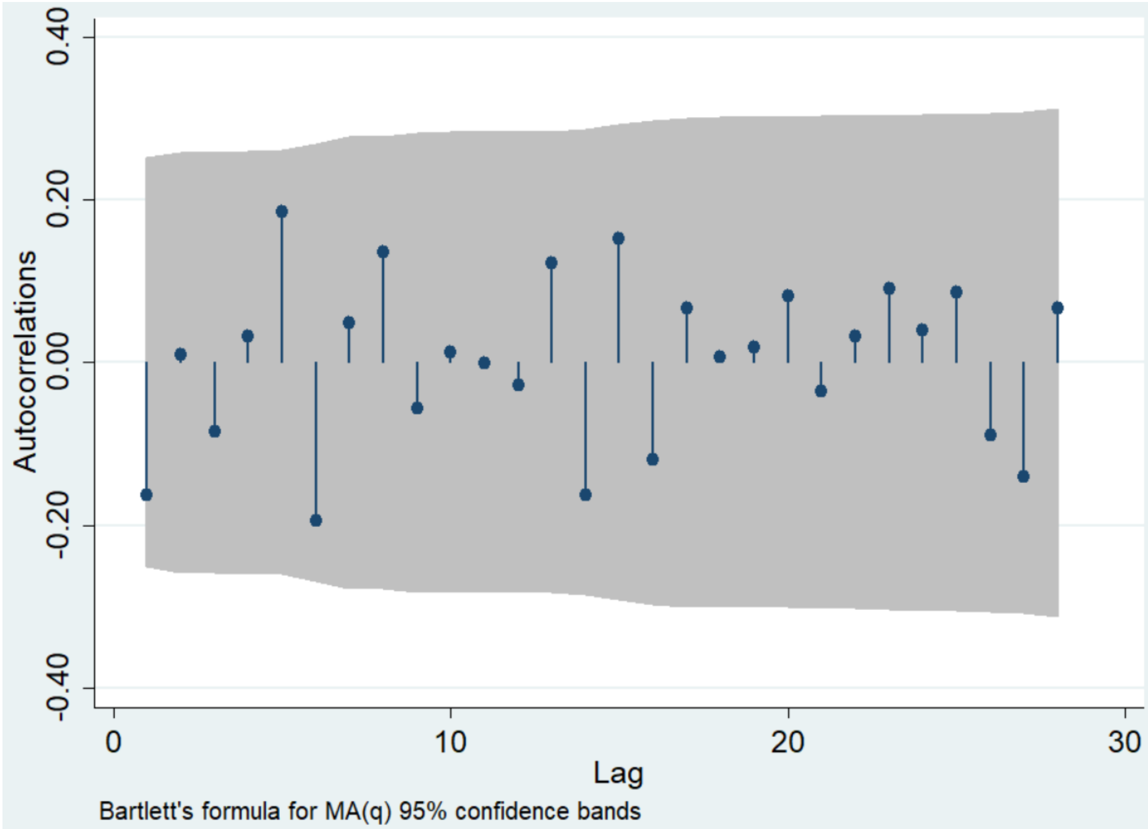

Figure 5.11. Graphed Autocorrelations of Burglary Rate(1,0,0) (1,0,0,12)

Bivariate Results

Having confirmed adequate univariate $ARIMA_{(p,d,q)}$ models for each variable, bivariate associations are used to determine whether VHR properties are a significant predictor for each kind of crime. Table 5.7 provides the aggregate results of three ARIMA models for VHR and each type of crime rate. The values presented in the table are the z scores from each of the three models. When VHR data are differenced to be stationary (Chamlin & Sanders, 2018, pp.326-327), and other series are corrected to account for autoregressive and seasonal components, VHR: All is found to have a non-significant (p>.05) relationship with each of the crime rate variables.

Table 5.7. Aggregated Bivariate Results of VHR: All on Crime DVs

Variables	**Substance Rate**[1]	**Disturbance Rate**[2]	**Burglary Rate**[2]
VHR: All Properties$_{(D)}$	0.39	- 0.44	- 1.19
Constant	7.36 *	16.57 *	10.35 *
AR$_{(1)}$	5.87 *	4.23 *	8.87 *
AR$_{(2)}$	1.31		
SARIMA$_{(1,0,0,12)}$		3.38 *	2.84 *
Observations	60	60	60
Wald χ^2	221.19 *	39.45 *	87.58 *
Box-Ljung Q, 12 df, p>.05			

* p<.01; [1] ARIMA$_{(2,0,0)}$; [2] ARIMA$_{(1,0,0)}$ SARIMA$_{(1,0,0,12)}$

Individual results for each of the distinct bivariate models are presented in the Appendix. Each of the models is found to be adequate in terms of portmanteau Q statistics, coefficient values, and ARMA significance. The substance rate variable represents the best available identification, despite the non-significant AR$_{(2)}$ component. The bivariate models are similar to the univariate models regarding model results. Additionally, these bivariate ARIMA results are similar to distributed lag models that were initially considered to understand these series associations.

Discussion

After analyzing each series of interest and relying on the Box and Jenkins approach to ARIMA models, there was a non-significant (*p* > .05) association between

VHR properties and each of the crime variables from 2014 to 2019. While several other approaches could have been used (e.g., Shrestha & Bhatta, 2018; Van Holm & Monaghan, 2021), this initial time-series approach indicates caution should be exercised regarding temporal precedence assumptions of VHR and crime. Figure 5.1 visually presented the substance crime rate to be an irregular series, perhaps influenced by temporally unique shocks, like legislative changes for substance crimes. VHRs predicting the substance crime rate beyond past months of the crime rate suggest tacit support for some temporal precedence claims, though it also warrants alternative approaches for disentangling this relationship. For example, if bi-directional associations are found cross-sectionally, structural equation modeling is one such method for understanding these relationships (Kline, 2015).

Initial distributed lag models (DLMs), not shown here, found similar results to the ARIMA results, though the ARIMA results also allowed for greater nuance to be identified regarding seasonal components and required fewer pre-test transformations.[60] Both in the univariate and bivariate models, the disturbance rate and the residential burglary rate had 12-month seasonal aspects, and autoregressive aspects. The rates were influenced by the same conditions affecting rates 12 months apart, in addition to the rates being affected by immediately previous months. This is consistent with the crime seasonality literature (Baumer & Wright, 1996; Farrell & Pease, 1994; Linning et al., 2017). The substance rate series was not seasonal, though drift was observed in the series and the middle of the series is less stable. One potential reason for this is that the political and legal climate of drug enforcement was in flux in central Texas during this time

[60] For example, the *VHR: All* and *Substance Crime* variables both require transformations to be normally distributed for DLMs.

(Plohetski, 2019). For example, in 2018 federal law changed regarding hemp. In 2019 Texas legalized some forms of cannabis, and the Austin Police Department has had shifting policies regarding CBD and marijuana possession (Menchaca, 2020).

Several data and variable characteristics are important to consider in time-series models, and one of them is collinearity (Pickup, 2015). While previous research found that listing type is an important consideration when geographic analyses are used (e.g., Reinhard, 2021; Roth, 2021b; Xu et al., 2019), collinearity issues prevent meaningful analysis of multiple listing variables in the same time-series models. These issues also prevent different results from crime-bivariate models using different VHR variables. These five years of data from Austin, Texas indicate that the total number of VHR properties was increasing consistently, as were VHRs in which the entire structure was rented, and VHRs in which only one room in the structure was rented. While this confirms the increased presence, and likely popularity, of VHR properties (Binns & Kempf, 2021), this also causes the different listing type series to be analogous when measured monthly from 2014 to 2019.

One of the central issues encountered in this study is commonly encountered in econometrics in general: non-stationarity. Non-stationary data must be transformed to be stationary for most time-series models (Enders, 2015; McDowall et al., 2019). While different approaches are available to correct for non-stationary data (Enders, 2015; Pickup, 2015), differencing was selected here as most apt despite its limitations. By taking the difference of $Y_{(t)}$ and $Y_{(t-1)}$, one observation is removed and variation is reduced in the data overall. Table 5.9 provides the contrasted descriptive statistics between the differenced and non-differenced VHR data.

Table 5.8. Descriptive Statistic Contrast Regarding Differenced VHR data

Variable	**N**	**Mean**	**Std. Dev.**	**Min (Max)**
VHR: All	61	15,847.07	6101.36	5039 (21167)
VHR: $All_{(D)}$	60	293.7	432.02	- 526 (2124)

In the differenced data, the range of values among observations is less than the range of values among non-differenced observations. With less variation among observations, associations are harder to detect statistically, and this may explain the non-significant results found in this study using ARIMA modeling and distributed lag models. However, the data must become stationary in order to model associations in a nonspurious manner (Enders, 2015, p.195). Phrased another way, differencing reduces the likelihood of finding significant results, but if differencing was not used, the significant results found would not be accurate. These spurious results, not shown here, were significant and underscore the importance of framework selection and addressing data concerns (Shrestha & Bhatta, 2018).

Several reasons likely exist for why the VHR data are currently non-stationary. The principal reason could be that Airbnb, and vacation home rentals in general, are a newer phenomenon that is still seeing growth (Binns & Kempf, 2021)-at least in Austin, Texas, and at least from 2014 to 2019. In econometric literatures, stationarity was not observed for some phenomena until over 100 years of data were collected (e.g., Enders, 2015, pp.211-214; Rogoff, 1996). It could be that when the count of VHR properties stabilizes, after some unknown quantity of time in the future, it is easier to predict and ascertain relationships between VHRs and crime or other conditions. It could also be that in other locales, the adoption of VHR properties were greater initially, prompting less fluctuation in subsequent years.

One implication of the results and the data is that current predictions and temporal understandings about VHR properties may not be generalizable. This unreliability supplements the unreliability associated with the years 2020 to 2021 and the COVID-19 pandemic, which greatly influenced the tourism and rental market in additional ways (e.g., Škare et al., 2021). The time-series data indicate that the average of rental properties varies greatly from year to year; there is no reliable average annual value that can accurately be used to understand VHR properties, at least in the city used for this analysis. It is unknown whether this trending quantity of VHRs populate regions in a uniform or non-uniform manner. For example, if VHR properties are increasing in quantity, it is unknown if this increase proportionally affects each census block group, neighborhood, street, and so forth. Perhaps early adopters of VHR properties were in affluent neighborhoods, and later adopters were in middle-class neighborhoods or those with greater racial heterogeneity. This is one of many directions that future research may go to understand rental properties and crime.

This study is the first to analyze VHR and crime with time-series, and one of few to analyze VHR and crime in a temporally relevant manner (e.g., Ke et al., 2021; Van Holm & Monaghan, 2021). The results underline the need to use methodologically diverse approaches to assess these properties. Several studies have been conducted from persons of different disciplines, using different methods, in different locations (e.g., Roth, 2021b; Van Holm & Monaghan, 2021; Xu et al., 2019), and the results from the totality of them are inconsistent. The non-significant results found with this study, paired with the trending non-stationary data, suggests that generalizability is complicated for VHR research. This has been explicitly asserted by others (e.g., Maldonado-Guzmán, 2020, p.12) using different methods. Numerous kinds of facilities have been found to be significant predictors of crime (e.g., Cozens et al., 2019, pp.8-9), and so far, VHR properties do not appear to reliably be one of them. Results from 2016 data may or may not be generalizable to 2017 if the area is experiencing a surge of VHRs as Austin, Texas did from 2014 to 2019. For geographic analysis, data may not be generalizable if VHR properties are not proportionately appearing in the selected spatial unit of analysis over time. For example, it is unlikely that temporally surging counts of VHRs appear uniformly across all census block groups in a city.

Future research may pursue several directions given the results presented here. First, it is possible that these results suggest that the location of VHRs is more important than simply the frequency of VHRs throughout the city. Alternatively, future research should consider whether multiple properties owned by the same individuals overtime are differently associated with crime compared to owners of single properties (Lee et al., 2021). Second, the percent of all housing units in Austin that are VHRs increased overtime from approximately 1% in 2014 to over 5% in 2019,[61] though these estimates do not consider the type of housing unit, such as condominiums, multi-family structures, single-family homes, or mobile homes (see e.g., Wuschke & Kinney, 2018). The associations between VHRs and crime are more complex than the notion that increasing VHRs increases exposure risk to VHR relevant crime (for a similarly framed example

[61] These were calculated with annual housing unit estimates and the greatest monthly count of VHR properties in the corresponding year. In 2014 this equates to 5229 VHRs and 392,184 housing units. In 2019 this equates to 23,167 VHRs and 442,388 housing units. Note that this is likely an underestimate of VHRs given that properties each year may not be listed every month of that year.

using traffic incidents, see Chamlin & Sanders, 2018). Future research should differentiate housing types in a more thorough manner. Third, this study did not account for when the same properties were intermittently active throughout the study period. Future research investigating active VHR properties may find that continuously active VHR properties are less criminogenic than sporadically active VHRs due to underlying host or property characteristics (Arvanitidis et al., 2020).

VI. DISCUSSION

All cities have their Barksdale Markets. So its demise teaches us an important lesson: bad addresses can drive neighborhood crime.

-Linning & Eck, 2021, p.2

This discussion begins by summarizing each study and considerations of them collectively. Each of the studies considers VHRs in different manners, and each has its own strengths and weaknesses; these are addressed in the limitation section of this chapter. While some limitations are alluded to in each chapter, there are overarching limitations throughout. While the data in this dissertation are at the neighborhood level, a mixture of neighborhood and rental property recommendations and crime prevention considerations are presented. This section concludes with directions for future research.

Three studies were conducted to understand VHRs and crime, and the varying methods and units of analyses first require discussion. Figure 6.1 and Table 6.1 provide the monthly VHR counts, with the data for Chapters III-V indicated. The non-stationarity characterizing the VHR data in Chapter V suggests one potential reason that results may vary, even if the same methods had been used for all three studies. The average count of VHR: All increased 75.59% from 2016 (Chapter IV) to 2018 (Chapter III), 86.82% for VHR: Entire Structure, and 49.81% for VHR: Room. The crime data were comparatively more stable.

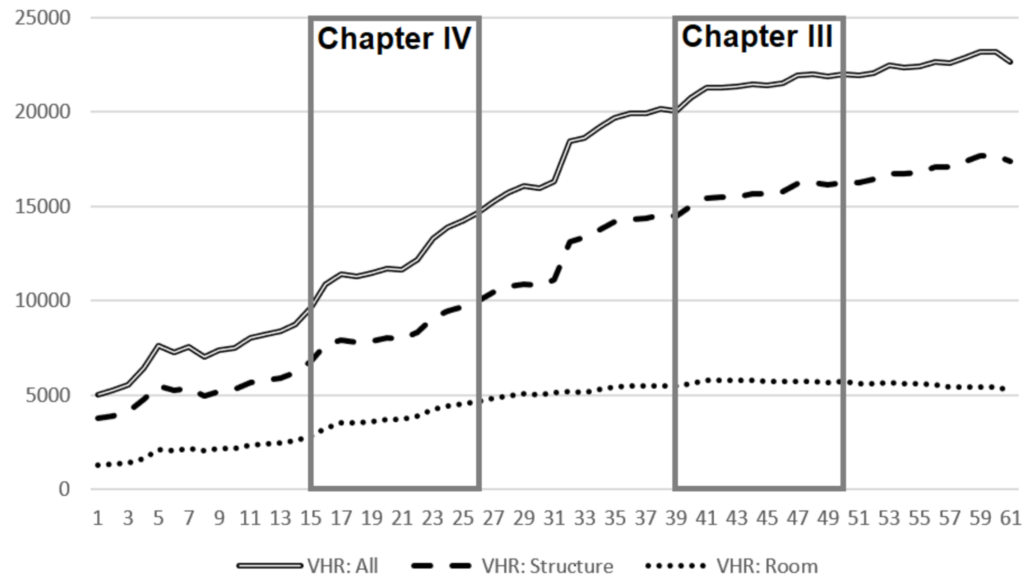

Figure 6.1. VHR Data for Chapters III-V

Table 6.1. VHR Mean Values for each Chapter

Section	Year	VHR: All	VHR: Structure	VHR: Room
Study 1 (Chapter III)	2018	21,407.25	15,655.25	5,707.5
Study 2 (Chapter IV)	2016	12,191.33	8,379.67	3,809.83
Study 3 (Chapter V)	2014-2019	15,847.07	5,707.5	4,351.56

Each crime type decreased and of a different magnitude than the VHR change. Figure 6.2 and Table 6.2 present the average values of crime rates for each of the crime types for each of the chapters. These rates were established based on the annual count of homes estimated from the American Community Survey. The average crime rate for substance crimes decreased 13.08% from 2016 (Chapter IV) to 2018 (Chapter III), decreased 16.62% for disturbances, and decreased 30.26% for residential burglaries. While each study timeline was constructed before in-depth analysis of data had been done, the 2017 substance crime rate average is much greater than either 2016 or 2018.

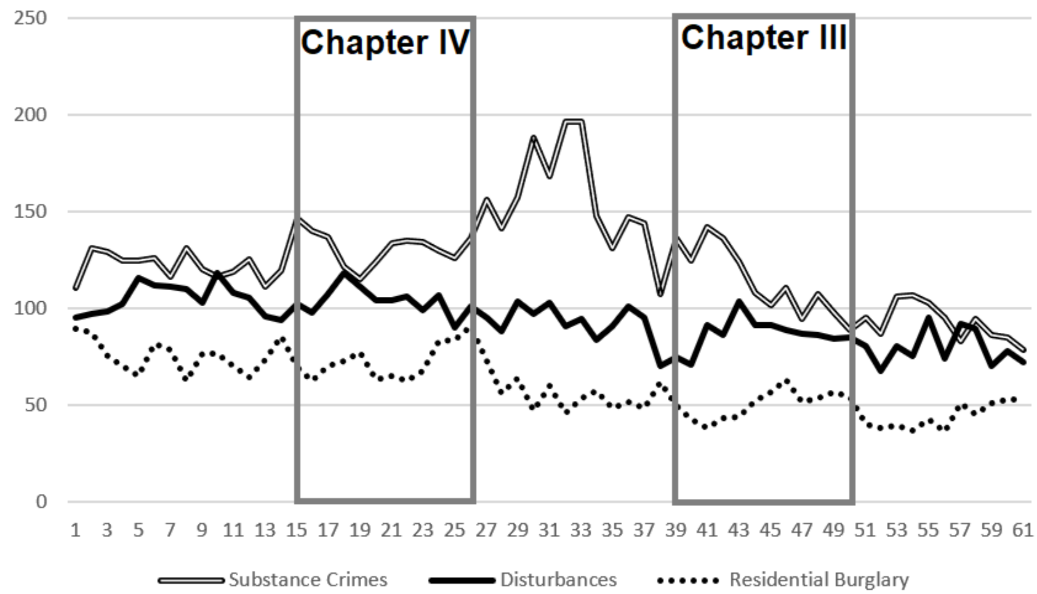

Figure 6.2. Crime Rate Averages for Chapters III-V

Table 6.2. Crime Rate Averages for each Chapter

Section	Year	Substance Crimes	Disturbances	Residential Burglary
Chapter III	2018	114.23	86.67	50.38
Chapter IV	2016	131.42	103.95	72.24
Chapter V	2014-2019	123.82	94.11	60.32

While each study is analytically more sophisticated than comparing frequencies, there are stark differences between VHR increases and crime rate decreases in the years analyzed. Chapters III and IV considered spatial concentration, social disorganization, and different neighborhood boundaries. Chapter V controlled for seasonal crime effects, and identifies the data generating process for each variable. However, in Austin, Texas from 2014 to 2019, VHR: All is linearly associated with time and is trending upward, while crime rates are comparatively stable or decreasing over the five-year period. The summarized VHR results of each chapter are presented below in Table 6.3.

Table 6.3. Results for each type of VHR property for Chapters III-V

Property Type	**Crime Type**	**2016 (Study 2.1)**	**2016 (Study 2.2)**	**2018 (Study 1)**	**2014-2019 (Study 3)**
VHR: All	Substances	+	+	-	NS
	Burglary	+	+	NS	NS
	Disturbances	+	+	-	NS
VHR: Entire Structure	Substances	NS	+	-	
	Burglary	NS	-	-	
	Disturbances	-	+	-	
VHR: Room	Substances	+	+	+	
	Burglary	+	+	+	
	Disturbances	+	+	+	

NS = not significant, p>.05
2.1 corresponds to CBGs, 2.2 to egohoods

Table 6.3 provides several conclusions about the influence of VHRs on crime, after controlling for neighborhood, bar, population, and dependency (lagged) variables. First, despite that all three studies were for the same city, results were not consistent across all VHR listing types and years. When considering all VHR properties across the three studies, there were 12 sets of results that produced six positive associations, two negative associations, and four non-significant associations. The listings could not be disaggregated for the time-series analysis in study 3, resulting in only nine sets of results for VHR: Entire Structure and nine sets of results for VHR: Room. For VHR: Entire Structure, there were five negative associations, two positive associations, and two non-significant associations. For VHR: Room, there were nine positive associations with crime-all VHR room associations assessed for both Study 1 and 2 were positive. One potential reason that Chapters III and IV found significant results and Chapter V did not is that the location of VHRs matters more than the count of properties. Even among properties found to be criminogenic spatially, place management may matter even more than location (Lee et al., 2021); these are the sorts of nuanced inquiries that future VHR research should pursue.

Second, despite all three studies were for the same city, results were not consistent among crime types. Table 6.4 below provides the crime types assessed in this dissertation across VHR types and years. For substance crimes, VHRs were positively associated with substance crimes in six models, negatively in two models, and non-significantly in one model. For residential burglary, VHRs were positively associated in five models, negatively in two models, and non-significantly in two models. For disturbances, VHRs were positively associated in six models, and negatively associated in three models. While Chapter V is not presented in Table 6.4, results were non-significant for each crime type in that study.

Table 6.4. Crime Associations Across VHRs and Years for Chapters III-V

Crime Type	VHR: All			VHR: Structure			VHR: Room		
	2016.1	2016.2	2018	2016.1	2016.2	2018	2016.1	2016.2	2018
Substances	+	+	-	NS	+	-	+	+	+
Burglary	+	+	NS	NS	-	-	+	+	+
Disturbances	+	+	-	-	+	-	+	+	+

2016.1 refers to CBGs, 2016.2 to egohoods

In studies one and two, data and correlations on VHRs and neighborhood characteristics were provided (Tables 3.3, 3.5, 4.4, 4.5). VHRs with only rooms rented were negatively but non-significantly correlated with median home value ($r=-.05$, $p>.05$), despite other VHRs being significantly and positively correlated. The significant and negative correlation between VHR: Room and median household income ($r=-.26$, $p<.01$) was stronger than with other VHR variables. VHR: Room was also not significantly correlated with concentrated disadvantage or residential instability, while entire structure VHRs were negatively correlated with both ($r= -.11$, $p<.01$; $r= -.12$, $p<.01$). All VHR variables were positively correlated with racial heterogeneity, though the correlation between VHR: Room ($r=.25$, $p<.01$) was slightly stronger than with VHR: Entire Structure ($r=.21$, $p<.01$). These results appeared again in Study 2, with VHR: Room being non-significantly correlated with concentrated disadvantage, despite significant and negative correlations between concentrated disadvantage and VHR: Structure ($r= -.15$, $p<.01$).

One interpretation of the above results is that while entire structure VHRs were in more advantaged neighborhoods with more stable residents, all VHR properties were more likely to be in racially diverse neighborhoods, though VHR: Room slightly more so than VHR: Entire Structure. In 2018 in Austin, Texas, VHR: Room produced about five-times less annual revenue, had a reduced occupancy rate, lower security deposit, and about three-times less daily income (Table 3.2). This suggests substantive differences exist, regarding both neighborhoods with the two types of VHR properties and among the VHR properties themselves. Another consideration is that the clientele that use these two types of VHRs are likely very different (LeBeau, 2012).

The most stable result across Studies 1 and 2 appears to be that after controlling for social disorganization variables, population, and spatial concentration, room rentals are more criminogenic than entire structure VHRs, regardless of crime type, year, or neighborhood operationalization. These results are predictable for a few reasons. First, considering the extant literature, rental costs are associated with crime and the clientele likely to rent (LeBeau, 2012). Persons renting individual rooms may be in different circumstances, and they may inadvertently be contributing to routine activity explanations of crime (Xu et al., 2021). Neighborhood residents who can afford to rent an entire structure may also have the resources to maintain the property (Roth, 2019) and operate in advantaged neighborhoods; places that are more likely to have informal social control and communal expectations about appropriate behavior that align with non-criminal activities (Browning et al., 2018). These more advantaged neighborhoods are likely to have greater ties between neighbors, perhaps facilitating communication about issues with a rental property. If crime or disorder are observed and a rental owner is contacted before law enforcement, issues may never be brought to the attention of law enforcement (and this study uses police data).

With spatially disaggregated data, it is likely that crime in neighborhoods is found to concentrate at rental properties, with greater crime concentration occurring at VHR: Room properties. This is a likely finding because that rental situation places rental guests in close proximity to rental hosts, allowing for victimization and offending of one group against the other (Binns & Kempf, 2021). This is in addition to guests in neighborhoods, places they have no social ties to or understanding of norms and customs. Hotels and motels, a different form of rental albeit with greater concentrations of persons, are discussed as risky facilities (Bichler et al., 2013; LeBeau, 2012). While not typically applied to spatial units as large as CBGs, *Chapter III* found evidence of incident clustering consistent with the law of crime concentration (Weisburd, 2015; Weisburd et al., 2016). A substantial percent of CBGs contained zero residential burglaries (23.3%), substance crimes (48.2%), and disturbances (14.6%). Incident frequency was also concentrated such that the 20% most incident prone CBGs across the city contained 78.4% of substance crimes, 58.6% of disturbances, and 57.7% of residential burglaries.

While Study 3 found non-significant results between VHRs and crime over five years, the trending nature of the VHR data produced several points worth noting. First, differenced data are less variable, and less likely to achieve statistical significance, which may partially explain the results. The non-stationary VHR data indicate that accurate long-term predictions and generalizations are complicated by the surge in properties in the city. Second, given the surge in properties, one criminologically-relevant question is what proportion of new properties is the result of the same owners renting more properties or new owners joining the rental market? This is of criminological importance because property management concerns may be relevant for uneducated, newer property owners, or among property owners unable to adequately maintain several properties (Payne, 2010; Rephann, 2009).

There are several methodological and analytic designs not employed here that future research may consider. While this study compared VHR listing types, this study did not employ risk terrain modelling (Caplan et al., 2011), or a spatial point pattern test (Wheeler et al., 2018). Aside from the worthwhile reasons to use meso geographic areas (e.g., Browning et al., 2018; Kubrin & Weitzer, 2003; Sampson et al., 2002), an additional reason is that data limitations prohibited address or street segment analyses.

With more granular data, future research may more reliably use a point pattern test, establish the law of crime concentration for VHR properties, or analyze VHR property management characteristics in relation to crime. Lastly, this dissertation used time-series analysis, seasonal ARIMA modelling, instead of other longitudinal, vector error correcting models, or panel modelling (Garcia et al., 2021), though panel models may be a sensible next step for determining how these properties are associated with crime across space and time (e.g., Van Holm & Monaghan, 2021).

This dissertation also did not use multilevel modelling with VHR characteristics and neighborhood characteristics (e.g., Deryol & Payne, 2020; Gilchrist et al., 2019), an approach that may provide a nuanced understanding of how collections of properties appear in some places. It would also allow for modelling property occupancy rates as they relate to neighborhood variables. Tillyer et al. (2021) found that crime generators (including hotels and motels) produce different levels of crime depending on neighborhood contexts. Their neighborhood variables included concentrated disadvantage, residential stability, vehicular traffic, and civic engagement. Ultimately they conclude that a combination of micro and meso geographic areas are necessary to fully understand *place in neighborhood* (PIN) concerns (see also Deryol & Payne, 2020). Boessen and Hipp (2015) conclude somewhat similarly (using ecological frameworks), that multiple concurrent units of analysis are necessary to understand some associations. Three Chapter III models with a concentrated disadvantage interaction variable are presented in the Appendix, and future research should consider more complicated neighborhood effects than what are presented here.

There are many available variables for Airbnb properties that were supplied alongside the variables used in this dissertation. Some of these variables were not considered here but may be relevant given other theoretical frameworks, designs, or interests. For example, individual VHR properties were assigned cleanliness ratings by guests who provided reviews; an inspection of the lowest scored properties may be useful, particularly as cleanliness relates to other kinds of property management or disorder concerns (e.g., Roth, 2019).[62] Similarly, the number of allowed guests, property photos supplied by the hosts, number of reviews, or properties with long minimum stays are all of potential future interest.[63]

Policy Implications and Crime Reduction

> …the scientist must be, as it were, mentally ambidextrous; fascinated equally on the one hand by possible meanings, theories, and tentative models to be induced from data and the practical reality of the real world, and on the other with the factual implications deducible from tentative theories, models and hypotheses.
>
> \- Box, 1976, p.792

There are several potential implications of the results presented throughout this dissertation. While *Chapter III* found a large disparity between reported rental properties in Austin, Texas in 2018 (n=2,185) and Airbnb listed properties (n=18,406), this section will instead concentrate on potential crime-reduction strategies.[64] Because this study

[62] Among the properties from 2009-2020 that had cleanliness reviews listed (n=25,210), 95.9% had scores of 8-10 on a 1-10 scale, and 4.1% had a score of 1-7 (n=1035).
[63] Among all Airbnb properties in Austin, Texas in these data from 2009-2020, 94.9% had minimum stays of 1-7 days, while 5.1% had minimum stays of greater than 7 days (n=2233).
[64] This dissertation does not address an extended discussion on regulation and raising awareness of unregulated VHRs because a meeting and communications in 2019 indicated that Host Compliance, a company that reports Airbnb properties to cities, had already begun working with city officials to identify

assessed VHRs in neighborhoods, neighborhood crime reduction approaches are first considered, and then individual property concerns. Neighborhood and address crime reduction are considered in light of VHRs; however, VHR research has yet to provide evidence-based examples of crime reduction strategies (e.g., with the EMMIE framework, Johnson et al., 2015). As such, these considerations are somewhat speculative and may be interpreted as directions for future research. VHRs are unique from ordinary considerations about rental crime (e.g., hotels/motels) and from ordinary considerations about vacant property crime. For example, attempts to minimize burglary at a dwelling (or in a neighborhood around a dwelling) assume that the burglar is not also regularly sleeping at the dwelling in the neighborhood.

The neighborhood approaches discussed here include gated communities, homeowners' associations, and a neighborhood management approach that incorporates place-in-neighborhood (PIN; Tillyer et al., 2021), and crime attractor concerns (Brantingham & Brantingham, 1995; Linning & Eck, 2021). The individual VHR considerations will consider the management framework ORCA (Eck & Madensen, 2018; Madensen & Eck, 2013; Weisburd et al., 2016, pp.46-50), situational crime prevention, and considerations about offender target selection of properties (e.g., Addis et al., 2021; Roth & Roberts, 2017).[65] Scholars who emphasize the importance of place management for crime reduction may characterize my aforementioned neighborhood approach as forcing property managers through controllers or super-controllers (Sampson

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all unregulated properties. Email correspondence is available upon request.

[65] Other approaches not taken here may have been equally useful. For example, a discussion on the importance of various kinds of neighborhood-adjacent risky facilities (Cozens et al., 2019; Tillyer et al., 2021), neighborhood street structure (Davies & Johnson, 2015; Summers & Johnson, 2017), and reducing repeat victimization (Farrell & Pease, 2017; Pease et al., 2018) are alternative approaches not taken here.

et al., 2010), while the address approach assumes place managers are likely to change without neighborhood, agency, city, or legislative levers (e.g., see Eck, 2017; Linning & Eck, 2021; Payne, 2017a; 2017b).[66]

One approach for considering crime in and around neighborhoods is gating communities While neighborhoods are typically understood as being public spaces without clearly delineated physical boundaries, a gated community may privatize public areas and have walls or fencing that more clearly identify access and ownership (Branic & Kubrin, 2018). Gating a community can be considered as a practical application of the CPTED principles of territoriality and access control (Cozens et al., 2019). Specifically, it is easier for residents to demonstrate ownership of an area, and protect an area from unwanted others when access is regulated through physical means (e.g., a password protected gate into the neighborhood). While the gated-community crime research is limited, recent studies have found that after considering neighborhood conditions, gated communities experience less burglary, violent, and property crime than non-gated communities (Addington & Rennison, 2015; Branic & Kubrin, 2018).[67] Whether gated communities are less socially disorganized or have greater collective efficacy is still unclear (Branic & Kubrin, 2018; Wilson-Doenges, 2000). It is likely that VHRs detract from crime prevention value that gated communities provide if VHR occupants are strangers to the neighborhood and are provided access in order to stay at the property.

A problem with this neighborhood crime reduction approach is that among the

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[66] Linning and Eck (2021) present a strong argument for how "neighborhood outsiders" (politicians, urban planners, real estate agents, investors, etc.) control crime in neighborhoods more than neighborhood residents themselves. While intriguing, it is outside the scope of this dissertation.
[67] However, these studies are far from definitive about gated communities always reducing crime in neighborhoods.

limited gated communities and crime research that exists, few consider rental properties. Some have asserted that gated communities only consist of owner-occupied homes, but no evidence can be found to support this assertion (Branic & Kubrin, 2018, p.409). Additionally, no studies could be found that considered gated neighborhood home rentals, like VHRs. Wang et al. (2021) found that rental housing (apartments) in a large Chinese city were positively associated with crime in gated communities, after considering a number of other housing characteristics (Wang et al., 2021, pp.2927-2928). While gated neighborhoods restrict access to the area and may reduce crime in high-crime VHR neighborhoods, if crime in these neighborhoods is driven by home renters who provide access to guests for the purpose of substance-fueled partying and revelry (Van Holm & Monaghan, 2021), the access restriction may not matter.

A second approach for neighborhood crime reduction that can act as a controller for address place-managers is neighborhood homeowners' associations (and "community crime watch" programs). These associations may be present in gated communities (Branic & Kubrin, 2018), but also in non-gated communities and can act as a form of shared governance of the neighborhood. Homeowners' associations and neighborhood crime watch programs appear to typically reduce crime and incivilities (Bennett et al., 2006; Louderback & Roy, 2018), and increase social capital and collective efficacy relevant considerations (e.g., Ruef & Kwon, 2016). Regarding VHRs, an owner letting their neighbors know about the nature of the property may help with reporting observed crime and disturbance issues at the property. However, research has yet to identify how these programs would affect rental property owners and guests in neighborhoods; if they can increase collective efficacy in neighborhoods, these programs may be a viable consideration for high-crime neighborhoods with VHR properties.

A third approach for neighborhood crime reduction could focus on first identifying the single properties within neighborhoods that disproportionately increase crime, and using multiple "levers" to shutter these properties, change ownership, or force compliance (Eck, 2017; Linning & Eck, 2021; Payne, 2017a). These properties may act as crime attractors, drawing in persons from other areas and supplying those persons with opportunities at the address and nearby for crime (Brantingham & Brantingham, 1995). It is possible that single addresses act as drivers to increase social disorganization; a property used by partiers, that fosters substance crimes and disturbance incidents, that draws potential offenders into the neighborhood, may cause nearby homeowners to not interact with other persons' nearby, and cause neighbors to leave the neighborhood.[68]

Like the other two neighborhood approaches for crime reduction, "[place manager] regulatory approaches have received little systematic study, though a number of evaluations show promising results" (Eck, 2017, p.157). The safety conditions in an area may hinge on a regulatory entity identifying the issue at the micro-scale, "wresting control" of the property or other micro-geography, and forcing change (Linning, 2019; Linning & Eck, 2021, p.42). Place-in-neighborhood (PIN) research is similarly relevant for high crime places in neighborhood contexts (Wilcox & Tillyer, 2017; Tillyer et al., 2021) and could be applied to reduce VHR crime. The premise is that by targeting the highest crime VHRs, VHR responsible crime in a city could be greatly reduced, and neighborhood crime, driven in large part by a highly criminogenic address, would also

[68] This was written to mirror Linning and Eck's (2021, p.1-3) account of a small convenience store that appeared to influence issues for blocks around the establishment through a combination of criminogenic place management, and optimal location for crime.

decrease. Tillyer et al. (2021) found that the same high crime facilities were differently influenced by social disorganization and neighborhood characteristics. Multilevel models may identify particular neighborhoods where VHRs are especially criminogenic and warrant targeted intervention. This nuanced identification is important: hotels and motels may produce more crime than single-family housing on average (e.g., Wuschke & Kinney, 2018), but within hotels and motels, some properties may be responsible for the vast proportion of hotel/motel crime in the city. Crime is concentrated among some kinds of facilities more than others, and within kinds of facilities (Blair, Wilcox, & Eck, 2017; Payne, 2017b).

In addition to the neighborhood-minded approaches for reducing VHR crime, suggestions are possible at the address level for homeowners using their properties as VHRs. One framework that place-managers (in this case VHR owners) can use is ORCA-organize space, regulate conduct, control access, and acquire resources (Eck, 2021; Madensen & Eck, 2013; Weisburd et al., 2016). Organizing space includes considerations about the location (such as transportation routes nearby, city parks, waterways), maintaining the structure, property, and CPTED-minded considerations about the property that increase visibility, display ownership, harden potential targets and facilitate support of legitimate activity (Cozens et al., 2019; Michaels et al., 2012). Regulating conduct at VHRs can be accomplished by clearly indicating acceptable and unacceptable uses of the property and noting the limits on what is tolerated without repercussion (e.g., noise ordinances or the presence of illegal substances). Hosts would also likely benefit from reporting crime incidents to the authorities, though it is currently unknown how likely this is to happen if owners are concealing their VHR property from the city to avoid tax and insurance requirements for rental properties. Controlling access at VHRs may take the form of indicating how many guests are allowed during each stay and how guests are expected to secure the property when they are present or absent. Lastly, *acquire resources* refers to how VHR owners can obtain the necessary assets to successfully carry out the previous three steps. The acquisition of resources at a VHR property can also be thought of as mindful considerations about the presence or absence of “hot products” (see Ekblom, 2013). Some products, such as flat-screen TVs, quality kitchen appliances, and other kinds of electronic goods, may represent ideal targets for theft given the access, inertia, value, and visibility of the items (Cohen & Felson, 1979). VHR properties are commonly furnished, and owners would benefit from have safeguards in place in case items are stolen by guests, or the property is burglarized.

Situational crime prevention (SCP) is another framework that could be applied to reduce crime at VHR properties (Cornish & Clarke, 2003). Through a combination of increasing the effort and risks, reducing the rewards and provocations, and removing excuses for crime, an owner can take practical steps to suppress crime in and around their property. More specifically, SCP is a crime prevention approach based off rational choice theory (Cornish & Clarke, 1987; 2003). Bichler et al. (2013, pp. 441-442) document 14 interventions at hotels and motels, and many of these interventions have SCP (and CPTED) elements. These include, altering check-in policies, staff training from the police department, clear code enforcement, and improvements to record maintenance. For VHRs, it could help to have clear rental agreements and posted rules (SCP, #21,22), limited greenery in front of the dwelling to assist surveillance up to the property alongside exterior CCTV use (SCP, #7,9), and background checks to screen out offenders. These situational factors can be highly relevant determinants of whether burglars choose that property (Roth & Roberts, 2017). Burglars may inspect trash at the property to ascertain characteristics of the items inside the dwelling, and the amount of visibility up to the front of the house greatly influences perceptions of risk for that property (Addis et al., 2021). VHR owners should be mindful of this and take steps to prevent their property from being identified as a profitable and low-risk target.

Limitations

> Since all models are wrong the scientist must be alert to what is importantly wrong. It is inappropriate to be concerned about mice when there are tigers abroad.
>
> - Box, 1976, p.792

Unsurprisingly, there are many limitations with the present research. These limitations are of varied kind and significance. Limitations are presented first that apply to multiple studies, and then secondly as they apply to individual studies. First, it is unknown how substantial edge effects, or MAUP, are in the present research, and this applies to both the boundaries of the city of Austin, Texas and the nature of CBGs instead of tracts, blocks, areal grids, and so forth (Lawton, 2018; Onubogu, 2013). The nature of the spatial unit is the boundary shape, area size, and relation of that unit, compared to adjacent others. It is worth noting that Chapter III relied on a different spatial unit of analysis than Roth (2021b) who used census tracts, and despite this difference, the results were similar. Additionally, Chapter IV results were similar between CBG and egohoods, which optimistically suggests a minimal influence of MAUP concerns. However, this study and others (e.g., Mletzko et al., 2018) may rely on city boundaries operationalized through regulatory boundary data provided by the city, through data provided by a certain law enforcement agency, or otherwise, and there is no simple solution to ascertaining what would be best (Brantingham et al., 2009; Rengert & Lockwood, 2009; Weisburd et al., 2016, pp.8-11). Because of this, there is a reliance on multiple imperfect solutions (Campbell & Stanley, 1963) through the use of different approaches in Chapters III - V.

A second limitation is that it is unknown whether the primary causal mechanisms proposed in this dissertation are true. Specifically, while this dissertation asserted that guests are the source of crime at VHRs in neighborhoods, facilitated possibly by poor management practices, it is possible that hosts have a more direct role in crime at properties (Binns & Kempf, 2021). While it is true that place managers have an important role in preventing crime (e.g., Payne, 2017b; Sampson et al., 2010), some place managers are criminogenic, and guests may be victimized. This dissertation is unable to disentangle the degree to which crime in neighborhoods from VHR properties were caused by rental guests, rental hosts, neighbors, or some combination.

A third limitation of the present research is the unsatisfactory variables available for social disorganization theory. Specifically, a substantial amount of research has recently included direct measures of social control and considered collective efficacy theory (see Sampson, 2011; 2017; Sampson & Groves, 1989; Sampson et al., 1997). Concentrated disadvantage, residential instability, and racial/ethnic heterogeneity interact with local friendship networks, peer groups, participation in community activities, and trust. These variables in turn may greatly affect neighborhood crime. A more refined examination of neighborhood conditions and VHR-on-crime research would establish the degree to which homeowners know each other, trust one another, and their willingness to intervene on each other's behalf. Homeowners have incentives to not report their properties to the city (DiNatale et al., 2018), and it is unclear how aware neighbors are to each other renting out their properties. Awareness of a property being a VHR may influence the amount of intervention neighborhood residents engage in when they see crime or disorder. Correlations in Chapters III and IV (Tables 3.5 and 4.4) found that VHR: Entire Structure was differently correlated with social disorganization variables than the correlations between the theory variables and VHR: Room; it is possible that a VHR listing-disaggregated approach is necessary to understand collective efficacy concerns in neighborhoods.

A fourth limitation was introduced by Chapter V results, pertains to Chapters III-IV, and other publications on VHRs: VHR research may not be generalizable across settings or years (Maldonado-Guzmán, 2020). Table 6.5 below provides correlations for 2016 and 2018 VHR data in CBGs in Austin, Texas. All correlations are positive and significant ($p<.01$), but variably so. For example, the VHR: All variable in 2016 is correlated with the 2018 variable ($r=.50$, $p<.01$), but less so than the correlation between the two VHR: Structure variables ($r=.97$, $p<.01$), or VHR: Room variables ($r=.89$, $p<.01$). The 2016 VHR variables possess stronger correlations with each other compared to the strength of the correlations within 2018 variables. For example, the 2016 VHR: Entire Structure correlation to 2016 VHR: All ($r=.98$, $p<.01$) compared to the 2018 VHR: Entire Structure correlation to 2018 VHR: All ($r=.43$, $p<.01$).

Table 6.5. Correlations of VHR properties in CBGs

Year (Chapter)	Variable	(1)	(2)	(3)	(4)	(5)
2016 (Chapter IV)	(1) VHR: All					
	(2) VHR: Entire Structure	.98				
	(3) VHR: Room	.80	.68			
2018 (Chapter III)	(4) VHR: All	.50	.48	.46		
	(5) VHR: Entire Structure	.95	.97	.66	.43	
	(6) VHR: Room	.76	.67	.89	.40	.69

This complicates VHR research and suggests that even when research is conducted by the same individual (e.g., compared to replications conducted by others, Farrington et al. [2019, p.382]) in the same city, results may vary. Results are not robust (Clemens, 2017; Duncan et al., 2014); they are highly dependent on a multitude of design decisions. This was observed in the discrepancies across Chapter III and Chapter IV results, despite both sets of egohood and CBG results being similar within Chapter IV. Fortunately, VHR research is currently novel, and perhaps after more research is conducted (and/or VHR frequencies stabilize over time and space), greater confidence may be found in how properties are associated with crime in certain settings or given certain spatial units of analysis.

Further limitations exist and have been enumerated at times throughout the previous chapters as they pertained to individual studies. For example, egohoods in Chapter IV must be constructed to either have a set radial distance (e.g., .25 miles) from centroids, or be constructed from polygon boundaries, and either approach is flawed for different reasons. The first approach means that gaps may exist regarding an egohoods' inability to cover an entire CBG (which are larger further from the city center), and the second approach means that egohoods are of variable size, modelled from CBGs which are of variable size. This is a poorly articulated and minimized limitation in other egohood research (Hipp & Boessen, 2013, p. 299).

Conclusion

The goals of this dissertation were simultaneously novel and simple: to contribute to the growing research on VHRs and crime, and then to ascertain whether VHRs contribute to crime above what is explained by social disorganization theory, bars, population, and autocorrelation (both spatial and temporal). While many approaches could have been taken, this dissertation used a three-study design to assess VHRs and crime in CBG neighborhoods, result robustness in a second study with CBG and egohood neighborhoods, and VHRs overtime in the final study. During this process, numerous limitations and directions for future research were provided.

This dissertation may be relevant to several kinds of stakeholders. The principal analyses being conducted with neighborhoods makes this work perhaps most applicable to community council groups, city regulators, homeowner's associations, and community-based organizations. Companies like Host Compliance can be used to help the city to identify unreported VHRs and maintain the city ordinance requiring short-term rentals to obtain annual operating licenses. VHR property managers and prospective renters would also potentially benefit, not just from this dissertation, but from the numerous sources of information pertaining to liability concerns, scams, and potential criminogenic conditions associated with the less-regulated sharing economy (see Binns & Kempf [2021] for an extensive discussion of these topics). For property managers and prospective renters, care should be exercised when considering this type of rental. While the results throughout this dissertation were somewhat variable, some general conclusions are available.

First, VHR listing type appears to matter more than crime type. For Chapters III and IV, VHR: Room was always significantly and positively associated with substance crimes, residential burglary, and disturbances. This was the case when CBGs or egohoods were used, and it was the case using 2016 or 2018 data. VHR: All was positively associated with crime in both CBGs and egohoods in 2016, but negatively or non-significantly associated with crime in 2018. VHR: Entire Structure was a combination of positively, negatively, and non-significantly associated with crime in 2016, though only negatively associated in 2018. Chapter V observed that VHR: Room was less non-stationary and accounted for a decreasing proportion of total VHRs overtime (e.g., 31.2% in 2016, but only 26.7% in 2018). Furthermore, VHR: Entire Structure had a stronger correlation in CBGs between 2016 and 2018 compared to VHR: Rooms, suggesting possibly greater spatial stability among VHR: Entire Structure properties at the CBG level of analysis. Correlations generally suggested that VHR: Room properties were neutral or positively corelated with social disorganization variables while VHR: Entire Structure properties were negatively correlated or only moderately positively correlated.

Second, the crime types were a combination of positively, negatively, or non-significantly associated with VHRs in negative binomial regression models and seasonal ARIMA models. Among the 30 modelled associations between crime and VHR properties (nine in Chapter III, 18 in Chapter IV, three in Chapter V), all three crime types had 5-6 positive and significant associations, 2-3 negative and significant associations, and 1-3 non-significant associations. No single crime type was consistently associated in the same way that VHR: Room was always positively and significantly associated.[69] Combined with the recent research on the importance of multilevel modelling and interactive effects for properties (Deryol & Payne, 2020; Tillyer et al., 2021), these mixed results may suggest that a more nuanced approach may be necessary to understand what causes these varying results that are not crime type specific.

Lastly, the results produced here provide a warning for future VHR research. The warning is that VHR-crime associations appear unstable, with the possible exception of VHR: Room properties. This is similar but not identical to conclusions produced by Maldonado-Guzmán (2020), Roth (2021b), and Xu et al. (2019). This dissertation mirrors Maldonado-Guzmán's (2020, p.12) generalizability concerns. This dissertation also somewhat mirrors Van Holm and Monaghan (2021) in that results were inconsistent across VHR listing types, crime types, and cities. However, whether this instability persists during or after the COVID-19 pandemic is yet to be seen (Roth, 2021c, pp.51).

[69] This statement excludes Chapter V as only VHR: All was used in that study.

APPENDIX SECTION

Research Ethics

TEXAS STATE UNIVERSITY

The rising STAR *of Texas*

March 22, 2021

Daniel Reinhard
c/o Dr. Mark Stafford
School of Criminal Justice and Criminology
Texas State University
San Marcos, TX 78666

Dear Daniel,

Your recently submitted IRB Determination Request Form was reviewed by Research Integrity and Compliance (RIC).

According to the provisions in 28 CFR § 46.102 "human subject" is defined as "a living individual about whom an investigator conducting research obtains (1) Data through intervention or interaction with the individual, or (2) Identifiable private information."

It is understood your research project exclusively involves the examination of several secondary data sources originally collect by a company known as "AirDNA", the Austin Police Department, and through the US Census website. It is understood the datasets are anonymous and publicly available. Furthermore, RIC is under the assumption the study does not involve interaction with living individuals or access to identifiable information. Therefore, RIC concluded your research does not use human subjects and is not regulated by the provisions in 28 CFR § 46.102.

If the subject pool or intent of your project changes in the future, please contact RIC to initiate an IRB assessment.

Feel free to contact me if you have any questions.

Regards,

Cristina A. Mendoza

Cristina A. Mendoza
Compliance Specialist
Research Integrity and Compliance
Texas State University
(512) 245-2314

OFFICE OF RESEARCH AND SPONSORED PROGRAMS
601 University Drive | Building and Suite | San Marcos, Texas 78666-4616 Phone: 512.245.2314 | fax: 512.245.3847 |
WWW.TXSTATE.EDU

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Figure 7.1. Research Ethics 2021

TEXAS STATE UNIVERSITY

The rising STAR of Texas

September 16, 2020

Daniel Reinhard
c/o Dr. Lucia Summers
School of Criminal Justice
Texas State University
San Marcos, TX 78666

Dear Daniel,

Your recently submitted IRB Determination Request Form was reviewed by Research Integrity and Compliance (RIC).

According to the provisions in 28 CFR § 46.102 "human subject" is defined as "a living individual about whom an investigator conducting research obtains (1) Data through intervention or interaction with the individual, or (2) Identifiable private information."

It is understood your research project exclusively involves the examination of secondary data (census data, public crime data, and anonymized data about vacation home rentals). It is understood the dataset is anonymous and publicly available. Furthermore, RIC is under the assumption the study does not involve interaction with living individuals or access to identifiable information. Therefore, RIC concluded your research does not use human subjects and is not regulated by the provisions in 28 CFR § 46.102.

If the subject pool or intent of your project changes in the future, please contact RIC to initiate an IRB assessment.

Feel free to contact me if you have any questions.

Regards,

Cristina A. Mendoza

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Figure 7.2. Research Ethics 2020

Chapter III, Variables for Table 3.2.

The average booked price over the Last Twelve Months. This includes cleaning fees distributed across the length of each reservation	**Daily Income**
Last Twelve Months listing revenue. Includes cleanings and daily rate but not other additional fees.	**Annual Revenue**
USD Listed Security Deposit	**Security Deposit**
The percentage of (days with a reservation) / (total number of days available or booked in months with at least 1 reservation) Calculation excludes blocked days and months where the property did not receive at least 1 booking	**Occupancy Rate**
Number of Unique Reservations in the last 12 months	**Number of Reservations**
The maximum number of guests the listing can acoomodate	**Max Guests**
The percentage of time a host responds to potential guests within 24 hours	**Response Rate**
The total number of days that a listing is available for rent, but not actually rented in the past year	**Unoccupied**
Percent of individual host ID with more than 1 property listing.	**% of Hosts with >1**
Percent of individual VHR properties owned by individual who owns >1 property	**% VHR owned in Collection**
Percent of individual host ID with more than 1 property listing.	**% of Hosts with >1**
Percent of individual VHR properties owned by individual who owns >1 property	**% VHR owned in Collection**

Figure 7.3. Variable Descriptions for Table 3.2.

Chapter III, Interaction of Concentrated Disadvantage (quartile)

Chapter III models for all VHR properties are presented here with an interaction variable for concentrated disadvantage on Airbnb properties. These models include the bars variable for all crime types. In order, the models presented are for residential burglary, substance crimes, and disturbances. The categories for this variable were quartiles with values of 1 to 4 in which 4 equals CBGs with concentrated disadvantage in the 75th to 100th percentile. Like the concentrated variable used in other models in this dissertation, a greater value of concentrated disadvantage indicates more concentrated disadvantage (e.g., greater CD means more families below the poverty line).

```
Negative binomial regression                    Number of obs     =        598
                                                LR chi2(11)       =     253.98
Dispersion     = mean                           Prob > chi2       =     0.0000
Log likelihood = -1435.2394                     Pseudo R2         =     0.0813
```

residentia~y	IRR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
airbnbs	.9993892	.0022805	-0.27	0.789	.9949294	1.003869
cd4_factors						
2	1.318862	.2116136	1.72	0.085	.9629914	1.806242
3	1.781449	.281241	3.66	0.000	1.307352	2.427473
4	2.044965	.3211636	4.56	0.000	1.503156	2.782069
cd4_factors# c.airbnbs						
2	.9966685	.0030157	-1.10	0.270	.9907753	1.002597
3	.9985487	.0028931	-0.50	0.616	.9928944	1.004235
4	.9996721	.0024144	-0.14	0.892	.9949512	1.004415
riscale	.7264054	.1972043	-1.18	0.239	.426673	1.236696
rh	.8376854	.2378508	-0.62	0.533	.480167	1.461401
bars	1.019961	.0087026	2.32	0.021	1.003046	1.037161
spatiallbu~y	1.000808	.00006	13.47	0.000	1.000691	1.000926
exposurehouseholds	(exposure)					
/lnalpha	-.3586466	.090669			-.5363546	-.1809386
alpha	.6986212	.0633433			.5848765	.8344866

Figure 7.4. Stata Output for Burglary and Interaction Effect in Chapter III

Negative binomial regression		Number of obs	=	601
		LR chi2(11)	=	309.68
Dispersion	= mean	Prob > chi2	=	0.0000
Log likelihood	= -982.62832	Pseudo R2	=	0.1361

substancec~s	IRR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
airbnbs	1.000624	.003289	0.19	0.849	.9941985	1.007091
cd4_factors						
2	3.38474	.888675	4.64	0.000	2.023203	5.662539
3	3.792763	.9834655	5.14	0.000	2.281596	6.30482
4	4.647338	1.15809	6.17	0.000	2.851607	7.573887
cd4_factors# c.airbnbs						
2	.9915994	.0043813	-1.91	0.056	.9830492	1.000224
3	.9942077	.0042724	-1.35	0.176	.9858691	1.002617
4	.9977066	.0034379	-0.67	0.505	.9909912	1.004468
riscale	1.690305	.6747682	1.31	0.189	.7729761	3.696272
rh	.9219257	.3976757	-0.19	0.851	.3958469	2.147161
bars	1.06411	.0218651	3.02	0.002	1.022106	1.107839
spatiallsu~e	1.006592	.0006193	10.68	0.000	1.005379	1.007807
exposurepopulation	(exposure)					
/lnalpha	.3090701	.1024828			.1082075	.5099326
alpha	1.362158	.1395977			1.114279	1.665179

Figure 7.5. Stata Output for Substance Crimes and Interaction Effect in Chapter III

Negative binomial regression		Number of obs	=	601
		LR chi2(11)	=	235.69
Dispersion	= mean	Prob > chi2	=	0.0000
Log likelihood	= -2414.6105	Pseudo R2	=	0.0465

disturbances	IRR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
airbnbs	.9990904	.0023419	-0.39	0.698	.994511	1.003691
cd4_factors						
2	2.06016	.3477773	4.28	0.000	1.47982	2.868091
3	4.385774	.7578873	8.56	0.000	3.125746	6.153736
4	3.09138	.532765	6.55	0.000	2.205247	4.333587
cd4_factors# c.airbnbs						
2	.9938155	.0032792	-1.88	0.060	.987409	1.000263
3	.9920501	.0031811	-2.49	0.013	.9858348	.9983045
4	1.000548	.0025579	0.21	0.830	.9955474	1.005574
riscale	1.057982	.3223194	0.19	0.853	.5823119	1.922211
rh	.6919308	.2238087	-1.14	0.255	.3670599	1.304333
bars	1.053992	.018099	3.06	0.002	1.019108	1.090069
spatialldi~s	1.003603	.0003457	10.44	0.000	1.002926	1.004281
exposurepopulation	(exposure)					
/lnalpha	.2464869	.0629795			.1230493	.3699244
alpha	1.279522	.0805837			1.13094	1.447625

Figure 7.6. Stata Output for Disturbances and Interaction Effect in Chapter III

Chapter IV, Illustration Limitations for Egohoods

This illustration is of when egohoods are constructed from block centroids, producing egohoods of uniform size and shape (in this case, all ¼ mile radius for the 9 egohoods in the image).

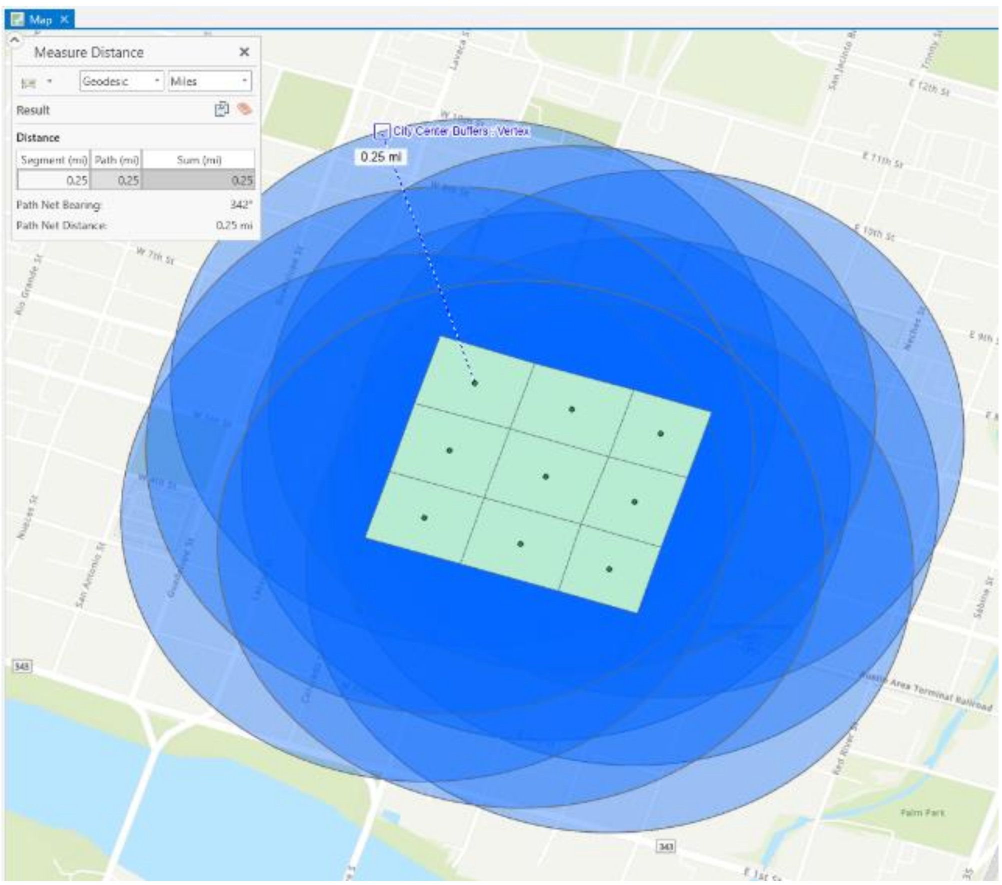

Figure 7.7. Egohood, Block Centroids, City Center

This illustration is of when ¼ mile buffers are constructed from the block boundary. Note that the distance from the centroid is 0.3 miles instead of ¼ mile. While the blocks are of similar size in the city center, they are not identical.

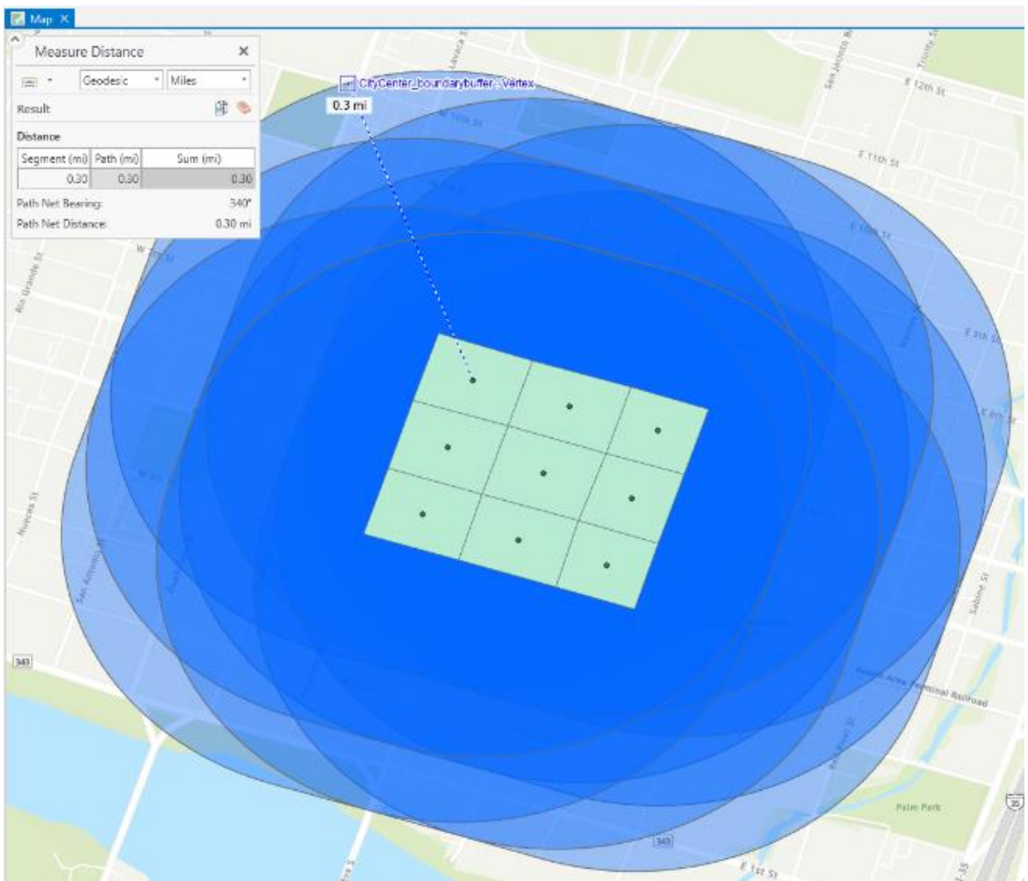

Figure 7.8. Egohood, Block Boundaries, City Center

This illustration is of the same ¼ mile radial buffer from centroids, but constructed closer to the city boundaries where the census blocks are now are highly irregular size and shape. This produces gaps in the city where incidents may occur and are not recorded.

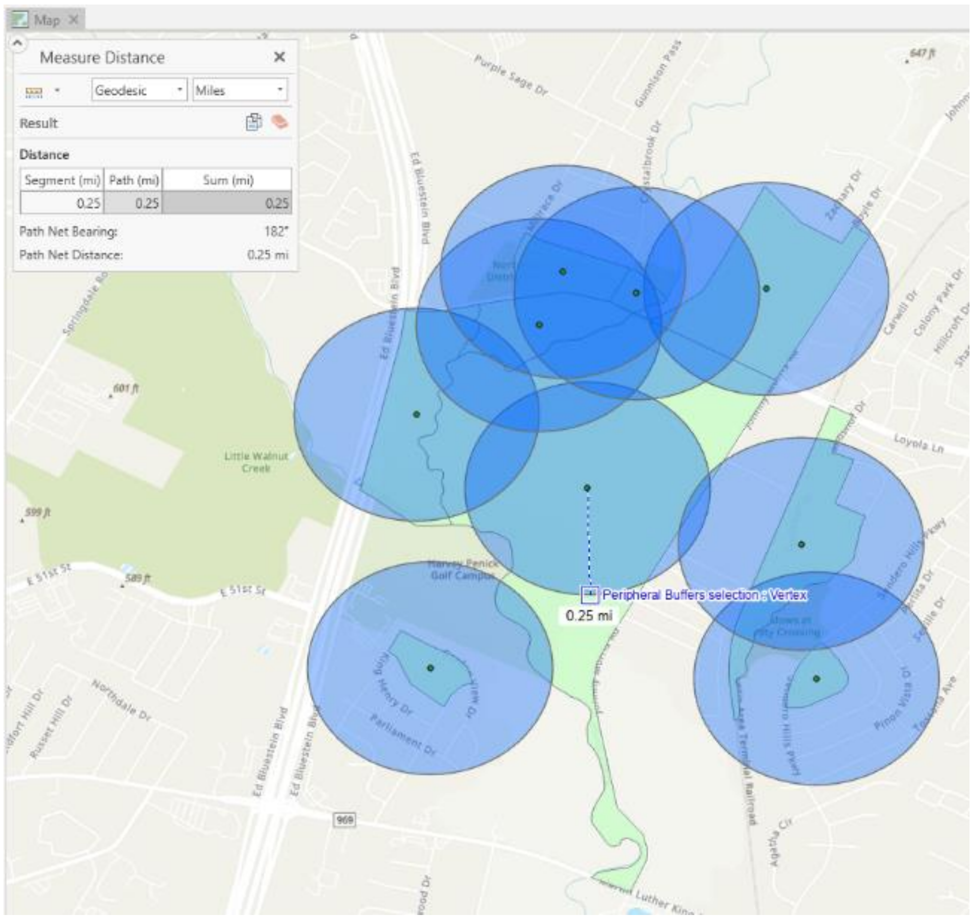

Figure 7.9. Egohood, Block Centroids, City Periphery

The natural solution, to create buffers from boundaries, then suffers the same MAUP issues as the blocks themselves: irregular size and shape. The 9 egohoods in this illustration are each of different dimensions, making comparisons between them potentially problematic.

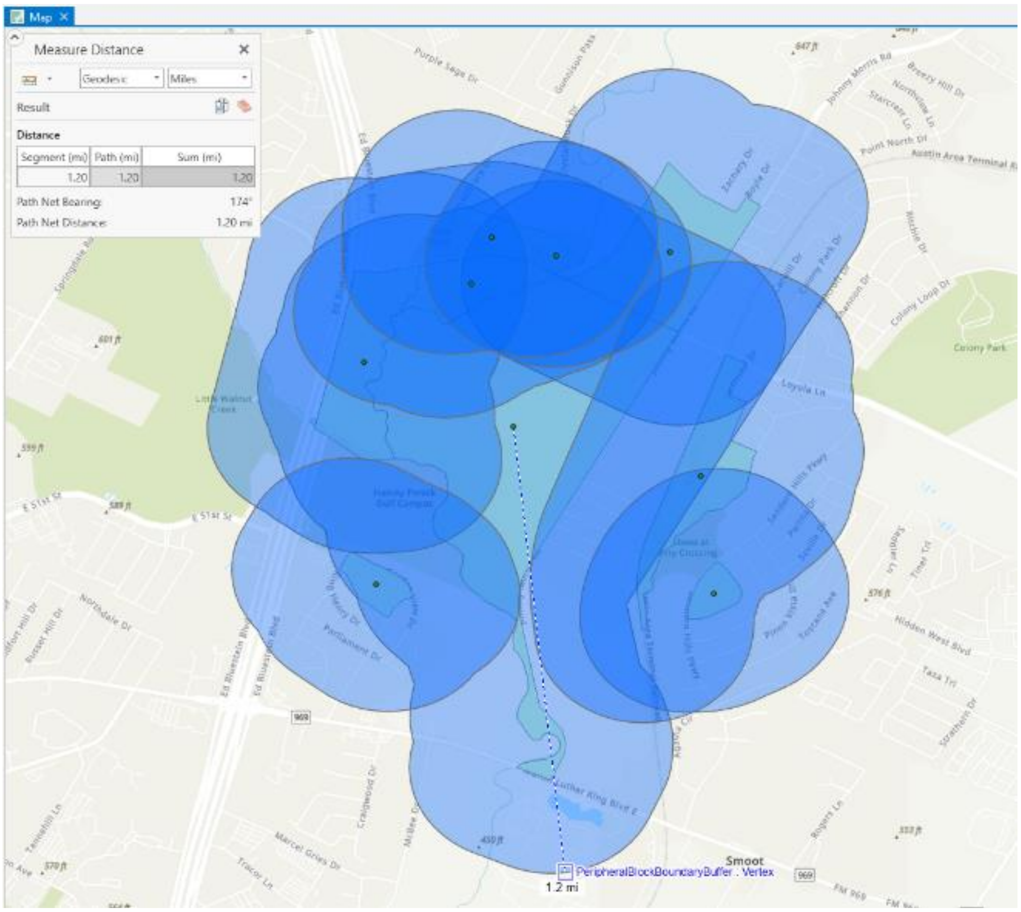

Figure 7.10. Egohood, Block Boundaries, City Periphery

Chapter IV, Temporary Accommodations

Temporary Accommodations

Data on hotels, motels, and other forms of temporary travel accommodations were obtained from a 2016 Austin Land Inventory. The land inventory dataset is publicly available and was downloaded from the Austin Texas Public Data Portal. The dataset is comprised of approximately 265,400 parcels in the city and contains land use descriptions. The dataset was first queried for the following terms, “hotel”, “motel”, “inn”, “B&B”, “bed”, “RV park”, “resort”, “suite”, “Hilton”, “Marriott”, “Embassy”, and “Ramada”. This resulted in 433 parcels. After duplicates were removed within the categories, and each search was consolidated, there were 223 temporary accommodations. This is similar to what was observed through Datafinity (n=198) and Visit Austin (n=227); however, this does not consider the number of rooms available per listing. The 223 listings were then geocoded.

Table 7.9. ARIMA(2,0,0) of *VHR: All* on *Substance Crime Rate*

Variable	Coefficient	OPG Std. Error	Z
VHR: $All_{(D)}$	.001	.003	.39
Constant	119.952	16.291	7.36*
$AR_{(1)}$	.704	.120	5.87*
$AR_{(2)}$	.162	.123	1.31
/sigma	13.975	1.165	11.99*

Wald χ^2 (2) = 221.19*
n = 60

* p < .05

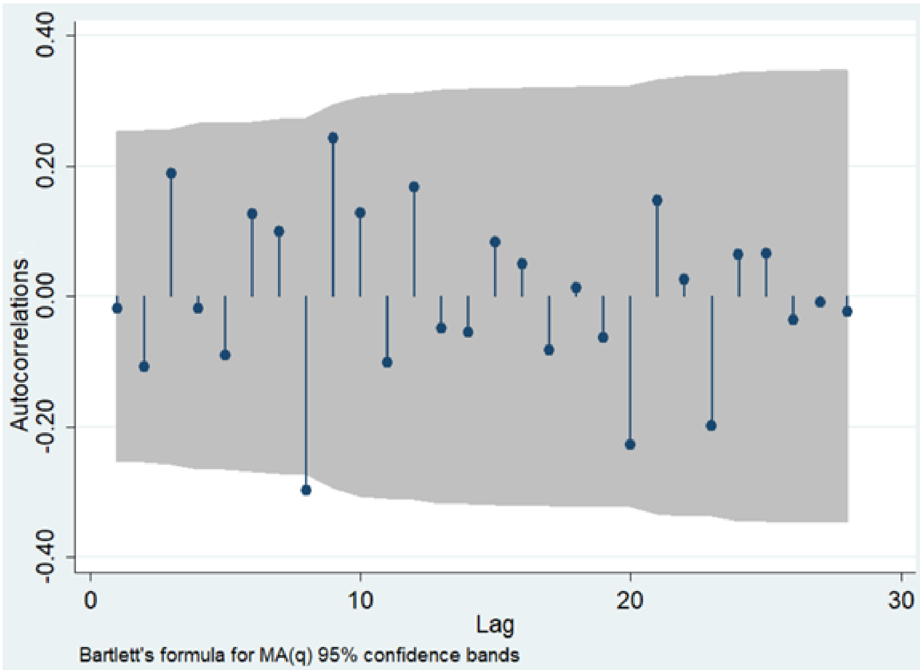

Figure 7.11. Graphed Autocorrelations of VHR on Burglary Rate(2,0,0)

Table 7.1. ARIMA(1,0,0) SARIMA(1,0,0,12) of VHR on Disturbance Crime Rate

Variable	Coefficient	OPG Std. Error	Z
VHR: $All_{(D)}$	-.002	.004	-.44
Constant	93.702	5.654	16.57*
$AR_{(1)}$	.636	.150	4.23*
$SARIMA_{(1,0,0,12)}$	.467	.142	3.30*
/sigma	8.338	.647	12.89*

Wald χ^2 (2) = 39.45*
n = 60

* p < .05

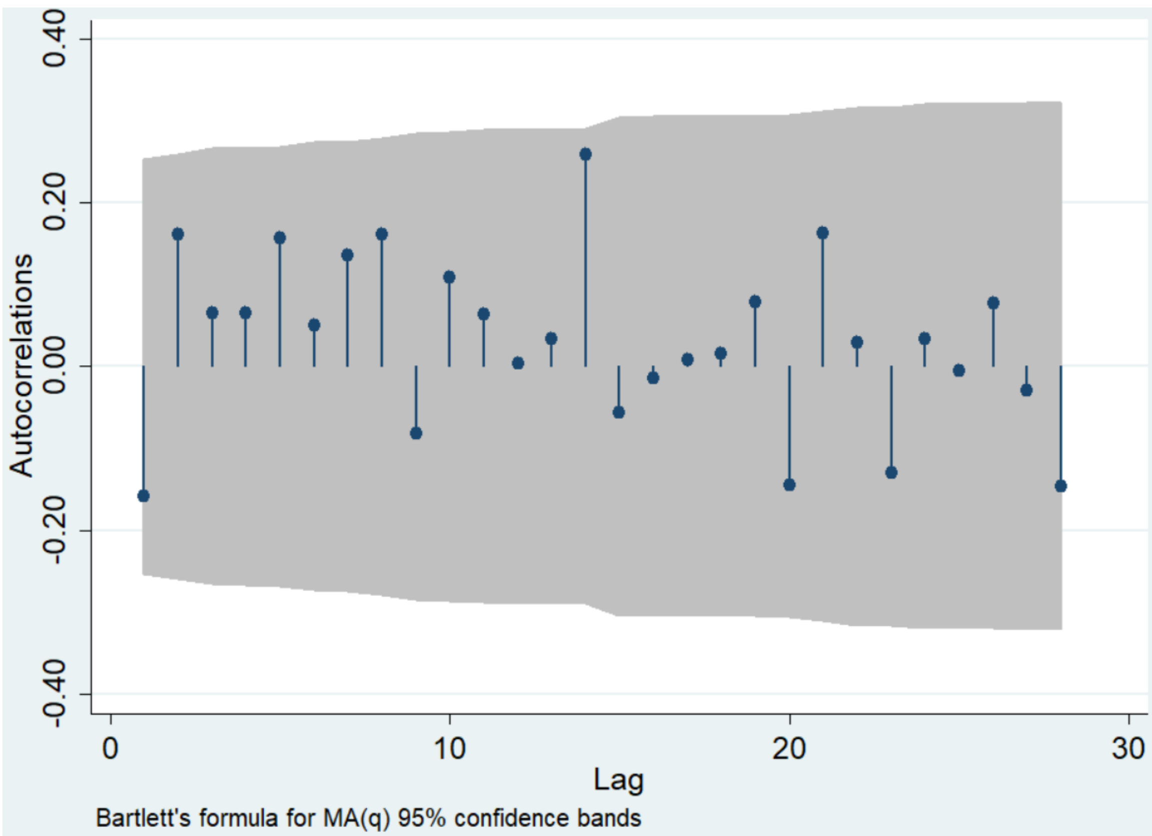

Figure 7.12. Graphed Autocorrelations of VHR on Disturbance Rate(1,0,0) (1,0,0,12)

Table 7.2. ARIMA(1,0,0) SARIMA(1,0,0,12) of VHR on Residential Burglary Rate

Variable	Coefficient	OPG Std. Error	Z
VHR: $All_{(D)}$	-.003	.002	-1.19
Constant	61.147	5.908	10.35*
$AR_{(1)}$	.782	.088	8.87*
$SARIMA_{(1,0,0,12)}$	.407	.143	2.84*
/sigma	7.788	.889	8.76*

Wald χ^2 (2) = 87.58*
n = 60

* p < .05

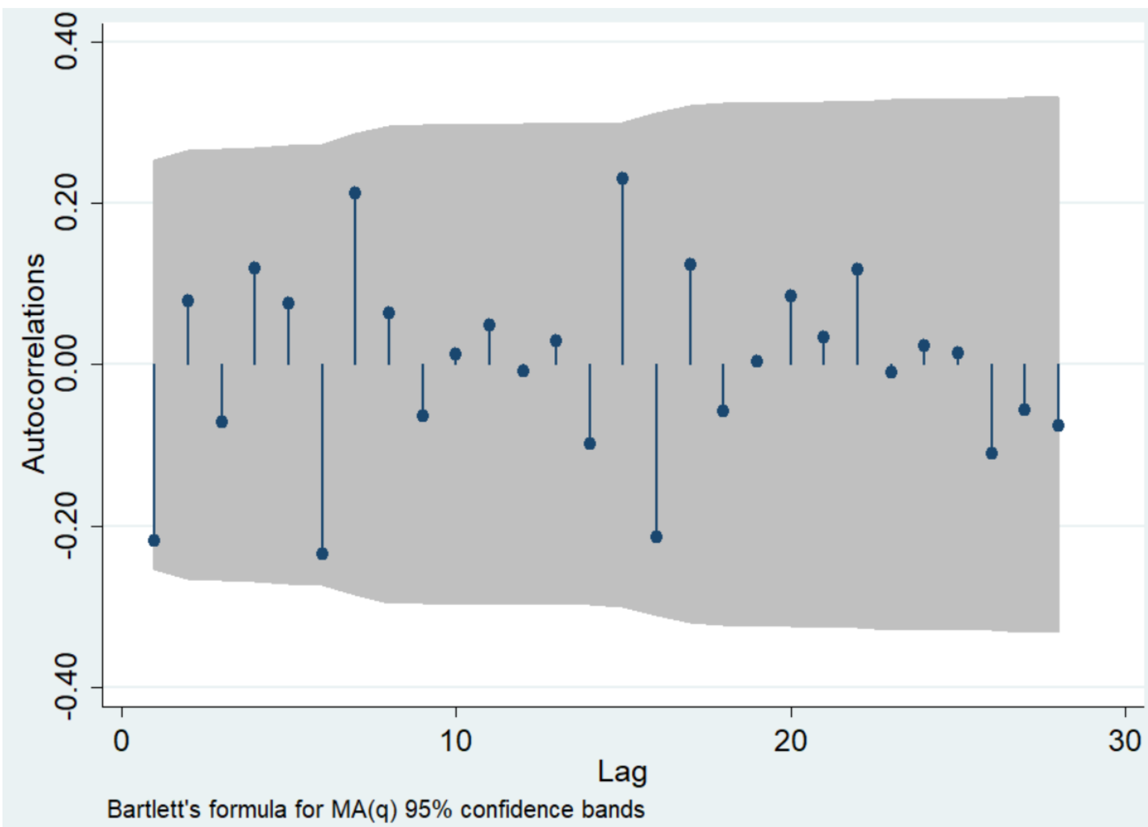

Figure 7.13. Graphed Autocorrelations of VHR on Burglary Rate(1,0,0) (1,0,0,12)

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