Investigating Spatial Relationships: Short Term Rentals and Criminal Activity

This manuscript is intended for submission to the Journal of Planning & Environmental Law

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Abstract

The expeditious growth of the US Short-Term Rental (STR) market, specifically Airbnb, has spurred waves of legislation targeting an exclusively commercial sub-set of STRs characterized as Non-Owner-Occupied Short-Term Rentals (NOOSTRs), driven in part by public perceptions of their impacts on residents in affected neighborhoods. Perceived impacts include reduced housing availability, increased rental costs, disruption of community dynamics, and an increase in nuisance criminal activity. Criminological theory indicates a lack of on-site guardianship, which may decrease as owners live further from rental properties, can result in conditions conducive to criminal activity. Previous studies of the relationship between criminal activity and STRs found positive correlations between these variables but did not specifically differentiate properties by proximity to an owner residence. Generalized Linear Regression (GLR) testing at the census tract level indicates weak but positive correlations between counts of NOOSTRs owned by both In-State and Out-of-State owners and criminal activity rates. Further GLR testing indicates a stronger relationship between criminal activity and Out-of-State owned properties than with In-State owned properties. By grouping crimes into National Incident Based Reporting System (NIBRS) types A and B, GLR testing indicates a greater correlation between all NOOSTR types and Crime Group B (less serious) incidents. Models that include additional socioeconomic variables, such as Poverty Level and Total Vacancies, better explain variation of criminal activity, but also result in diminished or inverted residual coefficients for NOOSTR variables. While results may be helpful for informing future legislation relating to mixed use neighborhoods, additional studies of the sensitivity of residential areas to the impacts of short-term rentals in neighborhoods with homogenous versus heterogeneous land use mixes would be beneficial.

Keywords: short-term rental, crime rates, Boston, Airbnb, NIBRS, owner proximity

Introduction

Since its inception in 2008, Airbnb has become one of the largest and most recognized names in the Short-Term Rental (STR) market. As of 2019, Airbnb offered more than seven million rental listings of homes, apartments, rooms, and vacation rentals in over 100,000 cities in over 220 countries (Airbnb, 2020a). Created as a room hosting site in 2008, Airbnb quickly expanded to apartments, houses, and vacation rentals in 2009 (Airbnb, 2020a). A result of this practice of expansion and development was the emergence of a new user type, the "professional host." Airbnb broadly characterizes professional hosts as any "host with multiple listings, who are managing teams, or anyone interested in growing a hospitality business on Airbnb" (Airbnb, 2020b). Airbnb now produces and promotes tools that support the management of multiple listings including management portals, pricing calculators, team collaboration portals, performance evaluators, and customizable "Pro" marketing pages (Airbnb, 2020b).

A more formal definition of a professional host is a host who rents out single or multiple units on a fulltime basis, excluding users who "rent out a spare room to supplement their incomes" (Wachsmuth and Weisler, 2018, pp. 1151-1152). The advent of the "professional host" has given rise to Commercial STRs, which are properties that lack the on-site presence of a property owner and are solely profit driven (Han and Wang, 2019). This lack of owner presence at Commercial STRs has led some municipalities to classify such properties as Non-Owner-Occupied Short-Term Rentals (NOOSTRs). The term "Non-Owner-Occupied" is borrowed from the mortgage industry where it denotes an investment property not occupied by the owner, typically apartments or multifamily dwellings (Kagan, 2020).

Prior to 2016, regulations affecting STR operations were often part of broader legislation addressing an array of issues that did not specifically target STRs. Between 2017 and 2019, municipalities across the United States began crafting and modifying ordinances to target STRs specifically, with particular focus placed on NOOSTRs. These ordinances were often in response to public outcry over the perceived negative effects of NOOSTRs on housing availability, rental rates, criminal activity, and the physical and social character of neighborhoods (Ferre-Sadurni, 2019; Bailey, 2016). By 2019, several major metropolitan areas including Los Angeles, Washington D.C., and Boston enacted ordinances restricting STR operations to the host's primary residence, effectively eliminating legal NOOSTRs (Simmons, 2020). In the same year, other municipalities of varying size, including Louisville, Santa Monica, Jersey City, Honolulu, and Austin, expanded existing STR ordinances to specifically restrict NOOSTRs (Simmons, 2020; Glowicki, 2019). Airbnb now actively campaigns against new NOOSTR regulations. In Jersey City alone, Airbnb spent approximately \$4.2 million on a failed campaign to prevent legislation that targeted investor-run listings (Ferre-Sadurni, 2019). The approximately 2,000 affected investor-run listings in Jersey City represented 75 percent of total listings and accounted for 91 percent of total revenue (InsideAirbnb, 2019).

Before legislation is implemented, voter sentiment must often first reach a point of criticality where widespread public opinion compels elected officials to act. The fact that numerous municipalities in different geographic areas reached this critical point during the same time period (2017-2019) indicates NOOSTRs are having market-wide effects and are not simply a localized phenomenon. Further confirming this shared, market-wide effect are the similarities in legislation and public opinion across affected municipalities. Jersey City, NJ claimed that Airbnb allowed "tourists to overwhelm residential areas, raising housing costs and mostly benefiting large-scale investors" (Feuer, 2020). The Mayor of Jersey City, whose office supported the ordinance, stated that "Airbnb was never intended to be the facilitator for full-time, for-profit illegal hotels, rooming houses, or illegal hostels in a community and unfortunately, in many instances, that is what it has become" (Conte, 2019). Jersey City's ordinance limited the number of days allowed for STR use to 28 in properties where the user was not the primary resident (Conte, 2019). Reports indicated that at the time of passage of the legislation, roughly 1 out of every 15 units in downtown Jersey City were NOOSTRs (Conte, 2019). Citizens of Louisville, KY reported frequent littering, drug use, and noise violations in NOOSTRs located in the city's historic districts (Bailey, 2016). Another cited problem was NOOSTR density, particularly in areas with high concentrations of STRs such as the Cherokee Triangle Historic Preservation District (Costello, 2019). Louisville City Councilman Brandon Coan confirmed in interviews that NOOSTR density was a key concern when crafting the city's new ordinance (Costello, 2018). The 2019 Louisville ordinance created 600 ft buffer zones around NOOSTRs and prevents the operation of additional NOOSTRs within the buffer area (Costello, 2019). Cherokee Triangle Association representative, Deirdre Seim, expects the ordinance will prevent NOOSTRs from surrounding full-time residents of an area while limiting changes to the physical and social character of their neighborhood (Costello, 2018). Las Vegas, NV also enacted

STR buffer zones at a similar size of 660 feet, but additionally banned the issuance of new NOOSTR permits (Johnson, 2018). Complaints leading to the Las Vegas ordinance included parking violations, noise violations, littering, and the use of residences as "party houses" for special events (Johnson, 2018).

After assessing these various complaints and ordinances, several common points emerge. First, NOOSTRs are commonly associated with non-violent criminal behavior, including parking violations, littering, drug/alcohol abuse, and noise violations (Bailey, 2016; Ferre-Sadurni, 2019; Feuer, 2019). Second, a perceived positive spatial relationship exists between NOOSTR counts and non-violent criminal behavior (Bailey, 2016; Feuer, 2019; Costello, 2019; Johnson, 2018). This study seeks to determine if the perceived connection between NOOSTRs and criminal activity that underpins legislation is accurate by determining what, if any, effect the new legislation has on existing crime rates.

Related Work

The criminological theories underpinning this study are Routine Activity Theory (Cohen and Felson, 1979), Rational Choice Theory (Akers, 1990), and Crime Pattern Theory (Eck and Weisburd, 2015). These theories also serve as the criminological basis of similar studies of the relationship between Airbnb and crime by Xu, Kim, & Pennington-Gray (2017) and Han and Wang (2019).

Routine Activity Theory revolves around the changes in and the convergence of three elements of criminal predatory violations: "motivated offenders, suitable targets, and the absence of capable guardians against a violation" (Cohen and Felson, 1979, p. 589). Cohen and Felson (1979, p. 589) define predatory violations as any "illegal act where someone definitely and intentionally takes or damages the person or property of another." The convergence in space and time of all three of these elements increases the likelihood of direct-contact predatory violations occurring even if structural conditions (the proportions of motivated offenders and suitable targets) remain constant (Cohen and Felson, 1979, p. 589). Therefore, a change in routine activity that results in the convergence of all three elements will increase the likelihood a crime will occur. A lack of on-site owners (guardians) coupled with frequently changing tenancy creates a situation that differs from the normal site conditions in residential neighborhoods. The presence of a NOOSTR effectively acts as a change in the routine activity of the neighborhood. NOOSTRs that host multiple guests have the potential to further concentrate all three elements within the NOOSTR itself. With occupancy in a state of constant and frequent turnover, the possibility of a convergence of elements becomes greater than when on a neighborhood scale, structural conditions remain more constant.

Crime Pattern Theory suggests that three additional controls, intimate handlers, guardians, and place managers, also influence criminal activity (Eck and Weisburd, 2015, p. 5). Intimate handlers are people who have the ability to influence motivated offenders and whose presence deters motivated offenders from committing crimes (Eck and Weisburd, 2015, p. 5). Guardians are anyone who protects suitable targets, while place managers "regulate behavior at the locations they control" (Eck and Weisburd, 2015, p. 5). If these three additional control types are either absent, ineffective, or negligent, then the risk of criminal activity increases (Eck and Weisburd, 2015, p. 5). In traditional home-sharing, the on-site owner can effectively act as all three control types, exerting a reductive influence on both internal (guest/guest) and external (guest/neighborhood) criminal activity. Through initial screenings, conversation, and check-in guidance, the owner becomes an intimate handler capable of influence. If a guest (potential motivated offender) is not from the area, the on-site owner becomes the primary point

of contact for local knowledge and assistance, which creates an influential relationship based on reliance. As a guardian and place manager, the on-site owner regulates site access and activity at the property both internally and externally. Neighborhood awareness, control over property access, and inperson monitoring helps on-site owners protect suitable targets from both external and internal motivated offenders.

Finally, Rational Choice Theory dictates that criminals will weigh the pros and cons of a crime before committing it, meaning a person is less likely to commit a crime if the "anticipated punishment outweighs anticipated rewards" (Akers, 1990, p. 671). This theory helps account for criminal activities such as drug abuse, alcohol abuse, and noise violations that do not have a clear "suitable target" element. The "absence of capable guardians against a violation" (Cohen and Felson, 1979, p. 589) at NOOSTRs means there is neither an authority present to witness criminal actions nor to implement punishment. By removing the fear of any site-based repercussions, the pro/con balance is upset in favor of the criminal activity.

Early STR studies focused on peer-to-peer home sharing exclusively and either did not differentiate between STR types or dismissed commercial STRs as extraneous (Adamiak, 2019, p. 1). A 2015 study by the Los Angeles Alliance for a New Economy (LAANE) indicated a considerable decrease in on-site hosting levels from October 2014 to July 2015, dropping from 52 percent of hosts to just 36 percent (Samann, 2015, p. 2). The same study also attributed 35 percent of Airbnb's Los Angeles revenue during this time period to just six percent of all leasing agents (Samann, 2015, p. 2). Other figures indicate that by 2016, professional hosting generated a third of all Airbnb revenue for that year (Stulberg, 2016). These figures indicate professional hosts occupy a considerable and increasing portion of the overall STR market.

A study by Xu, Kim, & Pennington-Gray (2017, p. 5-9) used geographically weighted regression (GWR) to analyze the spatial relationships between Airbnb locations and criminal activities at the county level and found a significant, positive spatial relationship between Airbnb and criminal activities. The same study also identified the existence of a positive relationship between the densities of Airbnbs and property crimes and a negative relationship between Airbnbs and violent crime. Airbnb housing type designations (Shared, Private, and Entire House/APT) superficially represent privacy levels but can also feasibly represent progressively decreasing levels of host access to guests. However, analyses utilizing these designations requires careful attention as ultimately these assignments are subjective selections made by hosts for listing purposes and are thus subject to varying degrees of crossover between categories. Levels of listing crossover for a geographic area may vary based on available housing types and how local hosts apply key descriptors to each listing type. For example, in an area predominantly comprised of multi-unit apartment buildings, an "Entire Apartment" listing may primarily refer to an entire domicile with no owner present. Conversely in a neighborhood comprised predominantly of single-family homes, "Entire Apartment" may primarily refer to a mother-in-law suite, accessory dwelling unit, English basement, or other structure that is separate, but still legally attached to an owner-occupied domicile. While technically "Entire Apartments", such examples could also be characterized as "Private Rooms" since they are technically part of a greater property. There is also no means to determine if a listing is commercial or non-commercial using only the listing types and this requires additional research into listing and property characteristics. As such, Xu, Kim, & Pennington-Gray also do not differentiate between commercial and non-commercial listings. Among Airbnb types studied, those rented as Shared Rooms had a higher correlation with crime than did those rented as Private Rooms or Entire

Homes/Apartments (Xu, Kim, & Pennington-Gray, 2017, p. 8). However, "Shared Room" is not an easily defined category and could vary from a pullout couch in a common space to a NOOSTR hostel with bunkbeds and no owner present. As the least private listing type, increased proximity between guests may play a greater role in the higher correlation levels than owner proximity to the property. While the results of the Xu, Kim, & Pennington-Gray's (2017, p. 9) study support the hypothesis that a connection exists between criminal activity and STR density, their use of counties as the scale of analysis makes it difficult to account for local environmental variables, such as variations in housing type, local economic conditions, and the spatial proximity of incident locations. Moreover, the findings were spatially heterogenous across the study area (Xu, Kim, & Pennington-Gray, 2017, p. 9), indicating that local variables may affect both the number and type of STRs and crimes.

A study by Han and Wang (2019, p. 8) found a positive association between commercial STRs and overall crime rates, where associations exist across all crime types. The same study also determined that no significant relationship existed between noncommercial STRs and violent crimes and showed limited associations with nonviolent crimes, such as weapon and drug violations. Unlike the study by Xu, Kim, & Pennington (2017), Han and Wang differentiated between commercial and noncommercial STRs; defining commercial STRs as properties used solely for profit where no owner is present. Han and Wang used the enactment of legislation restricting NOOSTRs in New York City, NY and San Francisco, CA as exogenic shock events around which they applied Difference in Difference (DID) analysis to quantify and compare the rates of individual crime types and STRs. Both ordinances only went into effect following lengthy litigation challenging the validity of the proposed measures. The San Francisco litigation resulted in a victory for the municipality, while the New York case ended in a settlement, resulting in loose enforcement (Han and Wang, 2019, p. 4-5). The intention of the New York and San Francisco ordinances examined in the Han and Wang study was to bolster enforcement of prior ordinances (originally passed in 2011 and 2014, respectively) by compelling Airbnb to share rental data and requiring all STR operators to register with the municipalities (Simmons, 2020). The 2011 New York State Multiple Dwelling Law made NOOSTRs illegal in apartment buildings and effectively required all apartment home-sharing to be the Shared Room Type (Xu, Kim, & Pennington-Gray, 2017, p. 3) by mandating unimpeded guest access to all areas (Simmons, 2020). This ordinance effectively banned NOOSTRs in the majority of New York housing units (apartment buildings) while forcing legal STRs to become Shared Room Types, which according to Xu, Kim, & Pennington-Gray (2017, p. 3), have a higher correlation with criminal activity. This timeline indicates that commercial STRs operating at the time of the Xu, Kim, & Pennington-Gray's (2017) study were either doing so illegally or were a non-apartment housing type. The 2014 San Francisco ordinance limited STRs to permanent residents, limited rentals to 90 days per year, and required residents to register rentals with the city (Badger, 2014). Prior to the passage of this ordinance, it was illegal to rental private homes for less than 30 days in San Francisco (Badger, 2014), meaning this ordinance effectively legalized Airbnbs in San Francisco. The subsequent modifications cited by Xu, Kim, & Pennington-Gray (2017, p. 4-5) attempted to compel platforms to provide listing information and confirm user compliance with city STR regulations (Farivar, 2017). As in New York, this original legislation was still in effect during the period that Xu, Kim, & Pennington-Gray (2017) studied, meaning that the commercial STRs they studied were operating illegally.

The county-level scale of analysis used by Xu, Kim, & Pennington-Gray (2017) weakens the ability of the study's model to explain the spatial relationship between criminal activity and STRs. In the areas studied there are substantial variations in topographic features, economies, architecture, and population

densities, all of which are factors that may influence not only the predominance of STR types, but also the preponderance of different crime types. An economically disadvantaged area with a surplus of available multiroom houses may be more conducive to both a specific STR type and criminal activity type without a causal relationship existing between the two. A more targeted approach using smaller study units may reveal more about the spatial relationships between criminal activity and STRs while minimizing the impact of external confounding variables on study results.

The Han and Wang (2019) study focuses on the municipalities of New York and San Francisco where STR legislation and litigation serve to complicate findings. While both are densely populated urban areas, each location has distinct characteristics developed in response to unique contexts. Roughly forty percent of buildings (many pre-WWI structures) in Manhattan alone do not meet building code requirements because they exceed limits for apartment density and height (Bui, Chaban & White, 2016). While the 2011 New York ordinance was the result of a decades-long progression of regulation to avert a housing crisis, the 2014 San Francisco ordinance and its subsequent modifications were reactionary instead of preventative. Decades-old "Cubic Air" restrictions prevent the construction of buildings over 40 feet in height in the city of San Francisco which, when coupled with the Silicon Valley tech boom of 2012, contributed to an extreme housing crisis that persists eight years later (Oatman-Stanford, 2018). The limitations placed on STRs in San Francisco were a reactionary attempt to keep additional long-term rental housing units on the market. The substantial differences in housing types, legal approaches, and economic situations call into question the validity of any comparisons made between these two municipalities. A housing crisis coupled with an influx of well-paid workers will likely lead to the displacement of vulnerable social groups as gentrification occurs. It is possible that STRs studied by Han and Wang (2019) were actually a blend of displaced residents seeking short-term housing solutions and traditional STR guests. It is also possible that new workers flooding into the area occupied STRs for varying lengths of time while searching for permeant accommodations. There is potential for an enormous event like the San Francisco housing crisis to produce non-generalizable results in a housingfocused study. Studying an area not affected by large-scale social or economic events would reduce the possibility of these unique factors affecting the results and provide more generalizable evidence about the relationship between STRs and crime.

Studies that attempt to differentiate between STR types face analytical difficulties caused by the spatial scales of available information and a general lack of differentiated data. Studying data aggregated at a non-optimal spatial scale or with comingled groupings of data types may be necessary due to limited data availability or the need to reach minimum sample size thresholds. Unfortunately, such compromises serve to obfuscate the spatial relationships between the studied phenomena. It is difficult to understand the spatial relationship between crimes and STR locations if the data are aggregated to a scale where the distance variation between locations becomes indeterminate. When undertaking studies that use the introduction of legislation to undertake a natural experiment, study periods are also difficult to establish since litigation often impedes the full implementation of STR-related laws. Matching study area characteristics is also critically important in studies that compare different cities since factors such as population density, primary housing type, and development history determine whether areas are commensurable. Area characteristics also influence the development of local STR markets. Market development influences public opinion, which in turn determines if future ordinances are preventative or reactionary in nature. To reduce these complications in future studies, several actions are necessary. First, the study area must not be the subject of a housing "crisis event" immediately before or during the

study period. Crisis events disrupt the "natural development" of local STR industries and have the potential to skew all associated data. The study should avoid areas in a perpetual state of crisis (constant low availability and high demand for housing) for the same reason. Second, the study area should not have highly skewed housing characteristics. A mix of housing types (apartments, houses, townhouses, etc.) avoids instances where an ordinance addressing a problem associated with a specific housing type has an overly broad effect due to a lack of housing type variation. Third, study data must be available at a spatial scale that allows for analysis of the spatial relationship between criminal activity and STR location. The spatial scale should be at a level that allows for the identification and analysis of NOOSTR clusters to better determine if NOOSTR density correlates with crime density.

Methodology

There are three phases that comprise this study: Data Assessment, Site Selection, and Analysis. Some portions of the Data Assessment and Site Selection phases overlap as data assessment leads to the exclusion of unsatisfactory sites. A thorough vetting of data and site quality conducted prior to the analysis phase reduces the potential for confounding factors that may adversely affect the quality of conclusions drawn from the analysis results. Another intent of the vetting process is to maximize the generalizability of the results by ensuring that the study site does not contain any unique structural and developmental characteristics. During the Data Assessment and Site Selection Phases we evaluated sites based on STR and Crime Data composition and availability, impact of rental regulations on listings, and housing type composition. The analysis phase consisted of two parts, Exploratory Analysis and Regression Testing. The first phase involved a comparison of NOOSTR listing rates and crime incident rates to determine if the two variables have a positive or negative relationship. The second phase is an examination of the two variables at the tract level, using a series of Regression Tests, to examine potential causal relationships between the two.

Data Assessment

Sources of publicly available STR data, such as scraping websites *InsideAirbnb* and *AirDNA*, focus primarily on Airbnb data, which will also be the subject of this study. Airbnb listed approximately fiftynine percent the total Online Travel Agency (OTA) housing stock as of 2020 (Transparent, 2020) and accounted for approximately 20% of all vacation rental booking across all platforms (Clifford, 2020) that year. Such market dominance makes Airbnb data a prime candidate for use in this study as it serves as a good representation of the industry as a whole. We began our data assessment by assembling and examining a list of available US datasets from each provider. To maximize study accuracy, acceptable datasets had to contain geocodable point location data with the majority of listings represented by "True" locations. Airbnb allows hosts a choice of displaying either a "True" location (accurate to within 500m) or a "False" generalized location (accurate to within 150m).

As the focus of this study is NOOSTRs, it is important that selected datasets contain sufficient information to identify this property type. To determine what information is necessary for their identification, we first examined what characteristics various municipalities (Seattle, Louisville, Boston, Nashville, San Francisco, New York) use to define NOOSTRs. Most simply define a NOOSTR as an STR that rents for less than 28 days at a time that is not the primary residence. Ultimately, we combined this broad definition with San Francisco's definition of a primary residence, which states that an owner must occupy the residence at least 275 days a year (defined as 3/4 of a year in the ordinance itself). So, for this study, we defined a NOOSTR as a property that is available for more than 90 days a year and is an

Entire Home/Apt room type, thus for proper identification of NOOSTRS, our data must contain stay duration, available days, and listing type (Shared Room, Private Room, Entire Home, Vacation Rental). We ultimately selected *InsideAirbnb* as our STR dataset provider after an examination of other sources revealed limitations stemming from a lack of data availability and cost-prohibitive usage fees. The dataset we chose to use also included additional information, such as Owner Location, which we used for more extensive examinations during the analysis phase.

Crime incident data is generally available in the form of yearly public reports provided by local police departments. These reports are normally available in CSV format and vary in both complexity and spatial accuracy. To be viable for use in this analysis the crime data had to contain geocodable point location data accurate to within a city block of the actual occurrence. More accurate location data helps avoid misleading cases of incident overlap that occur with utilizing centroidal location data. Geographic coordinates or city-style street addresses were both acceptable formats providing the addresses were geocodable. Individual incident reports had to include a National Incident-Based Reporting System (NIBRS)-compatible code designation (FBI, 2019, pp. 12-19). NIBRS is a federally recognized reporting standard developed by the Federal Bureau of Investigation that groups individual crime types by severity into two groups (A and B). Using this federally recognized standard increases study comparability and reduces relationship variability that can result from arbitrary crime category assignments, a problem with previously conducted studies on this topic. Incident date information, preferably both report date and incident date, were the final crime data requirements.

Site Selection

During the site selection process, we assessed sites based on housing composition, socio-economic events, and rental regulations by utilizing a variety of sources including local GIS repositories, American Community Survey (ACS) data, government publications, and newspaper periodicals. A preferred site contained diverse housing characteristics and was free from contamination by significant external influences for the duration of the study period. This required the exclusion of sites where external economic factors created or exacerbated housing crises, thereby creating conditions where the composition of STR occupants might deviate substantially from typical conditions. Selecting a site with diverse housing and neighborhood characteristics helps to ensure that laws pertaining to particular housing types do not tangentially affect the majority of the local STR market. Such was the case with the 2011 New York Multiple Dwelling Law, which primarily affects apartment buildings. Since apartments account for the majority of housing in New York City, this law effectively influences the majority of the STR market in the area.

We also researched STR rental regulations enacted at potential sites during the time of dataset availability to identify sites where regulations could potentially affect the number of STR listings at a quantifiable level. The pace of STR industry development varies greatly across locales often resulting in ambiguous, piecemeal regulations that lack legitimate enforcement provisions, penalties, or clear implementation guidance. Such factors can result in the presence of legal gray areas where hosts operate in open violation of the law thus reducing the measurable impact of regulation on the number of STR listings. To ensure a quantifiable effect and to avoid potential confounding effects of overtly illegal operations, an acceptable law must be a clearly defined, direct regulation of an existing activity with a fixed implementation date and enforcement provisions reinforced by defined consequences. We initially identified 20 potential sites of varying population size, housing unit makeup, and regional location for consideration. We narrowed the site pool further from 20 to 7, based on data availability, regulation acceptability, and timeframe alignment. Specifically, STR and crime incident data had to be available for six months prior to and after the effective regulation implementation date and all dates had to be free from confounding events. We then performed a comparative assessment of the 7 finalist sites comparing regulation strength, housing unit composition, and data readiness to select a location most compatible with our established site requirements.

Ultimately, we determined Boston, Massachusetts to be the most viable study site. In 2018, Boston crafted new STR regulations with the express purpose of banning investor STRs (NOOSTRs). The new regulations group STRs into three categories: Limited Share (room rental with host present), Home Share (entire residence with the host not present), and Owner-Adjacent (full unit in a two to three unit building with the host occupying an adjacent unit) (City of Boston Code §§ 9-14.2). For all three categories the city requires the property be the owner's primary residence, effectively banning the practice of using secondary properties as NOOSTRs (City of Boston Code §§ 9-14.5). The new regulations also require the registration of all STRs, while compelling websites, such Airbnb, to remove any listings not in compliance with city regulations and to provide the city with listing data to bolster enforcement (Valencia, 2019). The law went into effect on September 1, 2019 and the city began immediately to issue fines of \$300 to all identifiable, unqualified properties (NOOSTRs) (Valencia, 2019). Properties that met the qualifications for registration had to register with the city by December 1, 2019 to maintain their listing (Valencia, 2019). Following the final registration deadline, Airbnb executed a mass removal of unregistered properties per the new ordinance. This effectively provides two dates for comparison while meeting all other requisite site qualifications.

Data Preprocessing and Exploratory Analysis

In addition to the STR and crime incident data reviewed during the data assessment, we also utilized official Boston-provided datasets detailing open space, historic districts, and landmarks as well 2014-2018 ACS tract level sociodemographic and housing unit data from the US Census Bureau. Since the focus of this study is NOOSTRs, which lack an official industry definition, it was necessary to select criteria within the datasets to identify NOOSTRs per the definition we established during the Site Selection. This required the transformation of multiple datasets to identify NOOSTRs and further categorize them by Owner Location. We theorized that since many of the reported issues associated with NOOSTRs, discussed in the introduction, stem from a lack of property oversight, it would be beneficial to perform analysis based on owner-to-property geographic proximity (In-State vs. Out-of-State). We hypothesized that properties with more distant owners might provide conditions more conducive to crime occurrence.

InsideAirbnb provides scraped datasets in monthly increments, so after assigning a month and year field to each dataset, we merged them all into a single "listing" dataset ranging from June 2019 to June 2020. We selected this time period to put the final regulation's enforcement date of December 1, 2019 in the middle of the study period. We then standardized the point location data for each listing by taking the most recent listing's coordinates and applying them to previous listings with the same ID, assuming that newer coordinates maintain or exceed prior levels of accuracy. This ensured any aggregations would count multiple listings for a single location at consistent coordinates. Finally, we filtered the data to create a NOOSTR Listing Dataset including only Entire Home rentals and listings available more the 90 days out of the past 365 days as outlined in the Data Assessment. We also created a NOOSTR Single-Site

Dataset for deriving per structure averages during aggregations by removing listings with duplicate IDs from the NOOSTR Listing Dataset. The decision to exclude Shared Room and Private Room listing types stems from category definition and crossover concerns previously addressed in the Related Work section. Owner presence is difficult to ascertain for Shared Room listings types as this designation refers only to the level of privacy and provides no insight into the proportion of the overall property occupied by the rental space. While this category does indicate the presence of additional parties, these could equally be owners in the same rental space with guests, owners in other rooms with multiple guests in the rental space, or multiple guests in the same rental space and no owner present. Determining if a Shared Room is a NOOSTR with any level of confidence would require inspection of each listing to determine actual site conditions and the determination may still be limited by uninformative descriptive content or a lack of specificity in reviews. While Private Room listings may have some crossover between Entire Home/APT listings in certain cases, the designation itself is an indicator that only a portion of the overall property is occupied by the rental space. While the remaining portion could conceivably be occupied by additional tenants or unoccupied, the assumption for this study is the property owner will likely occupy these areas.

The exploratory analysis began with an examination of monthly event totals for In-State Owned NOOSTRs, Out-of-State Owned NOOSTRs, All NOOSTRs, Crime Group A, Crime Group B, and All Crime Groups through a series of histograms for each variable. We also developed persistency histograms detailing the number of NOOSTRs Added, Lost, and Maintained month to month throughout the study period. After examining the raw numerical data, we mapped the information, using the same categories, in a GIS for an assessment of the spatial distributions. Performing Hot Spot analysis on each variable for the full study period (no monthly divisions), we identified event concentrations, then overlayed those locations for comparison using the City of Boston-provided open space, historic district, and landmark datasets to better contextualize the spatial patterns. Some studies indicate "positive associations between urban green space and decreased violence and crime" (Bogar and Beyer, 2015), so we looked at open spaces as a potential influencing factor. Historic districts and landmark locations tend to be high traffic areas, so we also compared the proximity of crime incidents and STR concentrations in these areas as well.

Linear Regression Testing

In preparation for regression testing, we aggregated the NOOSTR Listing and Crime Incident Datasets to 2010 Census Tract level boundaries and calculated the average listing count, number of guests accommodated, minimum night stays, and yearly availability per tract. We calculated the monthly and yearly totals by tract to create dependent variables using the six categories from the exploratory analysis then drafted a series of monthly choropleth maps detailing graduated monthly totals to ascertain the stability of event concentrations over time. Again, we overlayed and compared this data using the three Boston-provided datasets to determine feature proximity. We then performed a series of Generalized Linear Regression (GLR) tests based on the Poisson distribution and utilizing all possible combinations of STR Ownership and Crime Incident variables using the calculated yearly totals to measure the baseline strength of relationships between and significance levels between the various variables.

We also sought to determine what effect additional socioeconomic factors that have been shown to have a relationship to crime levels have on the baseline measurement by selecting candidate

explanatory variables from the ACS tract level data, then performing additional GLR tests using multiple permutations of variable combinations. Ultimately, we selected Persons Below Poverty Level, Total Vacant Units, Males Age 14-18, Multi Unit (Buildings) 10+ Units, and Distance to Open Spaces as our core explanatory variables. Research indicated potential relationships between increased crime rates and Poverty Level and Total Vacant Units categories (Sackett, 2016). A similar positive relationship also exists between male youths and criminal activity (Laub & Sampson, 2003), but with considerable variation of intensity occurring amongst youth age groups (Teens, 20s, 30s) and specific crime group types (A and B). Teens and Males in their 30s were more disposed to the commission of Group B crimes while Males in their 20s had greater association to Group A crimes (Laub & Sampson, 2003). Given these variations, we chose to perform a full category assessment of all male age groups available in the Census tract data by building a series of individual regression models for all category divisions then selecting variables with a higher-than-average R-squared values for inclusion in the final multivariate models. Conversely, the Multi Unit 10+ and Open Spaces distance variables were found to accompany reduced rates of certain types of criminal activity, with Open Spaces having a negative relationship with both Crime Group A and B categories (Bogar & Beyer, 2015). Survey statistics show the Multi Unit 10+ variable has a specific relationship to burglary rates (Catalano, 2010) and given this narrow crime type association we chose to perform a full category assessment for the number of units category. After establishing the core study variables, we built 48 separate GLR models each containing different variable combinations. A systematic model building structure generally led to the early identification of confounding variables and those with minimal impact on statistical significance. Ultimately, we selected the models with combinations of variables with the highest explanatory power yet that were parsimonious for a final evaluation and assessment.

Results

Descriptive Results

From August 2019 (prior to the enactment of regulations on September 1, 2019) through November 2019 (prior to the registration deadline on December 1, 2019), there was a 16% decrease in total NOOSTR listings (*Fig. 1*) that coincided with a 18% decrease in crime incidents (*Fig.2*) over the same period. The sharp decline of NOOSTR listings in December 2019 (*Fig.1*) coincides with Airbnb initiating a bulk removal of unregistered properties. This outlier event immediately precedes a listing rebound that continues through April 2020, with listings peaking at the same time crime incident levels reach their lowest measured levels during the study period (*Fig.2*).





Figure 1. Monthly NOOSTR listing in Boston, MA

Figure 2. Monthly crime incident levels in Boston, MA

Plots of NOOSTR listing persistency show monthly growth rates of In-State Owner listings (*Fig.3*) exceeding Out-of-State Owner listings by 4.29% between December 2019 and April 2020. Both peak in April 2020 but consistent growth of In-State Owner listings (*Fig.3*) leads to an April 2020 growth plateau that exceeds the high figure set in August 2019. Conversely, Out-of-State Owner listings (*Fig.4*) plateau in January 2020 and do not again reach the previous peak reached in August 2019, before the implementation of STR regulations in September 2019.



Maps of In-State and Out-of-State owned NOOSTRs indicate higher concentrations of both NOOSTR types in areas of the city within a 1-mile distance from stadiums, commercial areas, convention centers, or medical facilities. During the study period the total number of In-State owned NOOSTR listings (9914) exceeded the total number Out-of-State owned NOOSTR listings (8647), yet Out-of-State owned NOOSTR (*Fig. 6*) concentrations were often denser than In-State owned NOOSTR (*Fig. 5*) concentrations by as much as 91%. The highest Out-of-State owned NOOSTR density area contained 2,852 more listings than the highest density In-State owned NOOSTR area. In-State owned NOOSTRs are more also more widely distributed than Out-of-State owned NOOSTRs, covering a total area approximately 10 square miles greater in size.



Figure 5. In-State owned NOOSTR distribution and density map

Figure 6. Out-of-State owned NOOSTR distribution and density map

Regression Results

Initial bivariate analyses in Models 1-4 (*Table 1*) yielded higher R² values when using Out-of-State owned NOOSTRs as an explanatory variable instead of In-State owned NOOSTRs for both Crime Groups A (7.85% vs. 5.26%) and B (17.11% vs. 10.65%). These figures indicate greater explanatory power for Group B crimes than Group A crimes for both In-State and Out-of-State owned NOOSTRs.

Table 1 – Bivariate Models

| Model | Dependent Var. | Explanatory Var. | Coefficient | SE | AIC | R² |
|-------|----------------|----------------------|-------------|----------|-------|-------|
| 1 | Crime Group A | In-State NOOSTRs | 0.002776 | 0.000055 | 40156 | 0.052 |
| 2 | Crime Group B | In-State NOOSTRs | 0.003929 | 0.000130 | 6910 | 0.106 |
| 3 | Crime Group A | Out-of-State NOOSTRs | 0.001231 | 0.000018 | 39090 | 0.078 |
| 4 | Crime Group B | Out-of-State NOOSTRs | 0.001676 | 0.000039 | 6470 | 0.171 |
| | | | | | | |

Subsequent multivariate modeling incorporated additional potential explanatory values as described in the Methodology section. Models 5 and 6 (*Table 2*) show that adding Persons Below Poverty Level, Total Vacant Units, and Multi Units 10+ increased the R² value an additional 30% for Crime Group A and an additional 23% for Crime Group B. Additional assessments of Models 5 and 6 showed that when Total Vacant Units were accounted for, the Multi Unit 10+ variable was no longer an important contributor to the model, resulting in the removal of the Multi Unit 10+ variable in subsequent models. A comparative assessment of all model permutations resulted in the selection of Models 7 and 8 (*Table 2*) as the most effective yet parsimonious models.

| ariate Models Dependent Var. | Explanatory Var. | Coefficient | SE | AIC | R² |
|---------------------------------|---|--|--|--|--|
| Crime Group A | Out-of-State NOOSTRS | -0.001384 | 0.011365 | 26617 | 0.382 |
| | Persons Below Poverty Level | 0.000640 | 0.000008 | | |
| | Total Vacant Units | 0.00328 | 0.000048 | | |
| | Multi Units 10+ | 0.000074 | 0.000011 | | |
| Crime Group B | Out-of-State NOOSTRS | -0.000779 | 0.000086 | 4908 | 0.402 |
| | Persons Below Poverty Level | 0.000583 | 0.000022 | | |
| | Total Vacant Units | 0.003107 | 0.000125 | | |
| | Multi Units 10+ | 0.000068 | 0.000030 | | |
| Crime Group A | Out-of-State NOOSTRS | -0.001107 | 0.000034 | 25256 | 0.415 |
| | Persons Below Poverty Level | 0.000440 | 0.000010 | | |
| | Total Vacant Units | 0.002966 | 0.000044 | | |
| | Males 14-18 | 0.000297 | 0.00008 | | |
| Crime Group B | Out-of-State NOOSTRS | -0.000719 | 0.000079 | 4834 | 0.413 |
| | Persons Below Poverty Level | 0.000581 | 0.000022 | | |
| | Total Vacant Units | 0.003304 | 0.000102 | | |
| | Distance to Open Spaces | -0.164766 | 0.031530 | | |
| | Crime Group A Crime Group B Crime Group A | Crime Group AOut-of-State NOOSTRS Persons Below Poverty Level Total Vacant Units Multi Units 10+Crime Group BOut-of-State NOOSTRS Persons Below Poverty Level Total Vacant Units Multi Units 10+Crime Group AOut-of-State NOOSTRS Persons Below Poverty Level Total Vacant Units Multi Units 10+Crime Group AOut-of-State NOOSTRS | Crime Group AOut-of-State NOOSTRS Persons Below Poverty Level-0.001384 0.000640 0.000328 Multi Units 10+Crime Group BOut-of-State NOOSTRS Out-of-State NOOSTRS Persons Below Poverty Level0.000779 0.000779 Persons Below Poverty LevelCrime Group BOut-of-State NOOSTRS Total Vacant Units Multi Units 10+0.000583 0.003107 Multi Units 10+Crime Group AOut-of-State NOOSTRS Persons Below Poverty Level Units 10+0.000068Crime Group AOut-of-State NOOSTRS Persons Below Poverty Level Units 10+0.000440 0.000440 Total Vacant Units Distance 14-18Crime Group BOut-of-State NOOSTRS Persons Below Poverty Level Units 14-180.000297Crime Group BOut-of-State NOOSTRS Dut-of-State NOOSTRS Persons Below Poverty Level Units 0.000304-0.000719 0.000581 Total Vacant Units Dut-of-State NOOSTRS Dut-of-State N | Crime Group AOut-of-State NOOSTRS Persons Below Poverty Level-0.001384 0.0006400.011365 0.000008 0.000008 0.000048 0.000074Crime Group BOut-of-State NOOSTRS Out-of-State NOOSTRS-0.000779 0.0000790.000086 0.000074Crime Group BOut-of-State NOOSTRS Persons Below Poverty Level Total Vacant Units Nulti Units 10+-0.000583 0.000125 0.000125 Multi Units 10+0.000120 0.000125 0.000125Crime Group AOut-of-State NOOSTRS Persons Below Poverty Level Units 10+-0.001107 0.0000300.000030Crime Group AOut-of-State NOOSTRS Persons Below Poverty Level Nales 14-18-0.001107 0.0002970.000079 0.000079 0.000008Crime Group BOut-of-State NOOSTRS Persons Below Poverty Level Nales 14-18-0.000719 0.000790.00079 0.000079 0.000008Crime Group BOut-of-State NOOSTRS Persons Below Poverty Level Total Vacant Units Nales 14-18-0.000719 0.0000790.000079 0.000079 | Crime Group A Out-of-State NOOSTRS -0.001384 0.011365 26617 Persons Below Poverty Level 0.000640 0.000008 Total Vacant Units 0.00328 0.000048 Multi Units 10+ 0.000074 0.000011 0.000011 4908 Crime Group B Out-of-State NOOSTRS -0.000779 0.000086 4908 Persons Below Poverty Level 0.000583 0.000022 10000125 10000125 Multi Units 10+ 0.000068 0.000030 25256 25256 Persons Below Poverty Level 0.000440 0.000010 25256 Persons Below Poverty Level 0.000440 0.000010 10000010 Total Vacant Units 0.00227 0.000008 4834 Males 14-18 0.000297 0.000079 4834 Persons Below Poverty Level 0.000581 0.000022 1000079 Crime Group B Out-of-State NOOSTRS -0.000719 0.000079 4834 Persons Below Poverty Level 0.000581 0.000022 1000072 1000072 Crime Group B |

Table 2 – Multivariate Models

The Exploratory Analysis indicated the presence of anomalies in the NOOSTR and crime incident data that could potentially affect results. In 2019, NOOSTR listings and crime incidents maintained a direct relationship in the form of a downward trend, but in 2020 the trend inverted with NOOSTR levels peaking (*Fig.1*) at the same time when crime levels reach their lowest point in the study period (*Fig.2*). Repeating Models 1 -4 (*Table 1*) using data from each year independently makes visible considerable differences in results for each period (*Table 3*). If this trend reversal is the result of an outlier event rather than a reaction to market forces, it could potentially impact result reliability and generalizability.

| Model Variant | Dependent Var. | Independent Var. | 2019 R ² Value | 2020 R ² Value | Percent Change |
|---------------|----------------|----------------------|---------------------------|---------------------------|----------------|
| 1 | Crime Group A | In-State NOOSTRs | 0.057424 | 0.030884 | -46.2176 |
| 2 | Crime Group B | In-State NOOSTRs | 0.065270 | 0.070878 | +8.592 |
| 3 | Crime Group A | Out-of-State NOOSTRs | 0.108449 | 0.040317 | -62.824 |
| 4 | Crime Group B | Out-of-State NOOSTRs | 0.122714 | 0.099893 | -18.5969 |

Table $3 - R^2$ Change from 2019 to 2020

Residual maps for Crime Group A (*Fig. 7*) and Crime Group B (*Fig. 8*) indicate clustering among tracts, with residuals more the 2.5 standard deviations below and above the mean, indicating that there are likely still missing explanatory variables. This is further confirmed by Global Moran's I spatial autocorrelation testing which resulted in elevated Z-Scores of 3.55 for Model 7 and 2.72 for Model 8. Crime Group B's results indicate less residual clustering than with Crime Group A and in both instances high residual areas often coincide with high density In-State owned (*Fig. 5*) and Out-of-State owned (*Fig. 6*) NOOSTR areas, indicating explanatory variables are still missing from the models.



Figure 7. Visualization of Model 7 residuals (Table 2)

Figure 8. Visualization of Model 8 residuals (Table 2)

For all NOOSTRs types, Crime Group B exhibits higher correlation coefficients than Crime Group A (*Table 5*). Of all the correlation coefficients only Out-of-State owned NOOSTRs and Crime Group B rise to what can be considered a moderate level between 0.3 and 0.6, with all others falling into the weak category at less than 0.3. However, if classified dichotomously with a mid-point division at 0.5, all results would fall into the weak category.

Table 5 – Individual Bivariate Correlation Coefficients

| Dependent Var. (X) | Independent Var. (Y) | Correlation Coefficient |
|-----------------------|----------------------|--------------------------------|
| In-State NOOSTRs | Crime Group A | 0.199 |
| In-State NOOSTRs | Crime Group B | 0.267 |
| Out-of-States NOOSTRs | Crime Group A | 0.277 |
| Out-of-States NOOSTRs | Crime Group B | 0.409 |

Discussion

Our literature review identified perceived associations between NOOSTRs and non-violent criminal behavior, including parking violations, littering, drug/alcohol abuse, and noise violations (Bailey, 2016; Ferre-Sadurni, 2019; Feuer, 2019). Such associations may also indicate a positive spatial relationship between NOOSTR density and non-violent criminal behavior (Bailey, 2016; Feuer, 2019; Costello, 2019; Johnson, 2018). Criminological theories, such as the Routine Activity Theory, Crime Pattern Theory, and Rational Choice Theory, support the notion that a lack of on-site supervision by invested parties can create an environment conducive to criminal activity. Another way of interpreting this concept is that as direct involvement by the most liable stakeholders decreases, so too does the level of oversight, which in turn results in increased criminal activity risk.

This can be expressed spatially in terms of distance from the owner's primary residence to the NOOSTR property. Tobler's First Law of Geography states that "everything is related to everything else, but near things are more related than distant things." Building on this concept of spatial proximity, we can surmise that as the distance between owner and property increases, the relationship between owner and property decreases. Effectively, the increase in distance and travel time to the property results in a reduction in direct involvement from the most invested stakeholder, the owner.

While owners may employ registered agents to manage properties in their absence, such agents can only be considered lesser stakeholders as they lack personal investment in the property. Since they do not reside on-site and are minimally invested in the property, a registered agent is unlikely to rise to the level of an intimate handler, capable guardian, or place manager as defined by the Routine Activity, Crime Pattern, and Rational Choice theories. It is for these reasons that we further subdivided the overall NOOSTR category based on In-State and Out-of-State ownership to further test this theory. While study results showed an overall weak relationship between NOOSTRs and crimes rates, there was a greater explanatory relationship (*Table 1*) and higher correlation coefficient (*Table 5*) for Out-of-State owned NOOSTRs and Crime Group B incidents than with In-State owned NOOSTRs. These results are consistent with this supplemental theory that increased distance between owners and NOOSTR properties increases the positive relationship between NOOSTRs and criminal activity, but additional analysis outside the scope of this study is necessary to determine if the observed trend would be observed for Owner Operated STRs as well. Research testing our theory regarding the relationships between NOOSTR density and Crime Group B rates revealed only a weak correlation between NOOSTR density and crime rates. This may be due in part to several incongruities within the research data involving its composition and collection. For example, Crime Group B does not include misdemeanor traffic violations other than Driving Under the Influence (DUI), so parking violations, a crime type consistently associated with NOOSTRs, is not included in the research data. This also means that other misdemeanor traffic violations potentially linked to NOOSTR density such as blocked driveways, fender benders, speeding, and automotive noise violations are also excluded from the study dataset. Another potential issue with "nuisance" type crimes (noise violations, parking violations, etc.) is underreporting, or at least the perception of underreporting. For example, authorities may receive multiple reports from independent parties about an incident, but only catalog it once to correspond with a single site visit. This increases public perception of the prevalence of the crime whereby the incident data is accurate but does not reflect the public's perceived impacts of the incident. Conversely, reporting and incident response practices relating to nuisance crimes may result in actual underreporting when responding to multiple incidents at a single location. Nuisance crime types may result in multiple site visits and unofficial warnings, which may ultimately be reported as a single incident, depending on how departments choose to catalog successive events.

Yet another data issue pertains to the study period. The observed 2020 trend change (*Table 3*) is likely the effect of COVID-19 response protocols initiated in March 2020 following the first recorded infection in Boston on February 1, 2020. A large reduction in public activity accompanied by an increase in the consistent occupation of domiciles due to shelter in place orders could explain the continued reduction in crime rates that began in 2019. An increase in In-State owned NOOSTRs might also be attributable to the same phenomenon since the quantity of STR listings in a given area is not specifically driven by market forces like supply and demand. Many municipalities also significantly reduced staff as part of the pandemic response, resulting in the suspension of some or all enforcement of non-critical regulations. These actions, coupled with a need to supplement income due to loss of employment and business closures, creates an ideal scenario for an increase in In-State owned NOOSTRs. The inflation of In-State owned NOOSTR stock may not have necessarily translated to an increase in rentals as pandemic protocols may have resulted in reduced occupancy rates. As this study focused on availability rates and not occupancy rates, additional research is necessary to determine what potential influence the condition and quantity of In-State owned NOOSTRS may have had on the observed reduction in crime rates.

There is likely not a simple way to completely account for the effects of a large-scale pandemic scenario other than to complete a new study in an area unaffected by pandemic protocols. Unfortunately, such protocols affected all final candidate sites identified in the Data Assessment and Site Selection process, leaving no alternative sites available for study. Most implementation dates for new STR regulations in the candidate sites coincided with the beginning of the 2020 calendar year due to either advanced crafting dates (late 2018 – early 2019) or delays in implementation due to litigation. However, looking at the 2019 data alone, the R² values did not rise above 0.13 (*Table 3*) in any combination of categories, indicating that any correction to 2020 data skewing resulting from COVID-19 would likely not alter results sufficiently to warrant changes to the study's conclusions.

There may also be a benefit in future iterations of this study to focus on areas where NOOSTRs, which effectively operate as commercial entities, drastically alter the existing designated neighborhood use dynamics. In this study, the areas of Boston with the highest NOOSTR densities were largely mixed-use

neighborhoods containing a combination of commercial and residential buildings, limiting the impact from the addition of more commercial properties. The presence of commercial establishments results in a regular influx of non-resident pedestrian traffic for commerce-related activities. While a large number of NOOSTR additions would likely have some quantifiable effect on non-residential commercial traffic, the perceived impact may be minimal given that such traffic is not a new phenomenon in that area. However, the addition of even a small number of NOOSTRs to a neighborhood zoned for single family residences would cause a fundamental shift in neighborhood use dynamics and effectively introduce non-resident traffic to the area. This type of variable introduction, representing a shift from non-existent to existent, as opposed to an incremental effect on existing phenomena, would likely have both a greater actual and perceived impact on the area and warrants further study.

Conclusion

While statistically significant, the correlation coefficients (*Table 5*) and R² results from the bivariate (*Table 1*) and multivariate (*Table 2*) analyses did not rise to a sufficient level of strength nor equilibrium to conclude that NOOSTRs and crime incident levels have any greater relationship beyond the tangential. Potential inconsistencies, addressed in the discussion, likely affected correlation coefficients and R² levels, but not to an extent that would alter conclusions. If we were to rerun our tests using extrapolated 2019 data in place of the existing, inconsistent, 2020 data, any relative increase would likely not rise to a level that would affect conclusions given the overall weakness of the results when stratified by year (*Table 3*). When we factor in the extent of clustering observed for Crime Group A (*Fig.7*) and Crime Group B (*Fig.8*) residuals, we can also conclude that there are additional, as yet unidentified variables or combinations of variables that better explain crime incident levels than those in the studied models. Considering the discussed limitations, it is possible that under certain specific site conditions NOOSTRs may have larger effects on crime incident levels, but it is also equally possible that a disconnect between perceived and actual impacts masks the fact the NOOSTRs have little overall impact

Resources:

Airbnb. (2020a) Fast Facts. Retrieved on 03/21/2020 from https://news.airbnb.com/fast-facts/

Airbnb. (2020b) Professional Hosting with Airbnb. Retrieved on 03/21/2020 from https://protools.airbnb.com/get-know-airbnbs-professional-tools-features/

Adamiak, C. (2019) Current state and development of Airbnb accommodation offer in 167 countries, Current Issues in Tourism, In Press, [Digital Article] DOI: <u>10.1080/13683500.2019.1696758</u>

Akers, R. (1990). Rational Choice, Deterrence, and Social Learning Theory in Criminology: The Path Not Taken, Journal of Criminal Law and Criminology, 81(3): 653-676.

An Ordinance Allowing Short-Term Residential Rentals in the City of Boston, City of Boston Code §§ 9-14.10 – 9-14.12 (2018)

Badger, E. (2014) How Airbnb just changed the housing laws in San Francisco. The Washington Post [Washington D.C.], 08 October 2014, [Digital Article]. Retrieved on 4/12/2020 from <u>https://www.washingtonpost.com/news/wonk/wp/2014/10/08/how-airbnb-just-changed-the-housing-laws-in-san-francisco/</u> Bailey, P. (2016). Airbnb rules rip neighbors apart. The Courier Journal [Louisville], 24 April 2016, [Digital Article]. Retrieved on 3/10/2020 from <u>https://www.courier-</u> journal.com/story/news/local/2016/04/23/airbnb-rules-rip-neighbors-apart/82800926/

Bogar S, Beyer K. (2016) Green Space, Violence, and Crime: A Systematic Review. *Trauma, Violence, & Abuse*. 17(2): 160-171. doi:<u>10.1177/1524838015576412</u>

Bui, Q., Chaban, M., & White, J. (2016) 40 Percent of the Buildings in Manhattan Could Not Be Built Today. The New York Times. 20 May 2016 [Digital Article] Retrieved on 4/13/2020 from <u>https://www.nytimes.com/interactive/2016/05/19/upshot/forty-percent-of-manhattans-buildings-</u> <u>could-not-be-built-today.html</u>

Catalano, S. (2010) "National Crime Victimization Survey: Victimization During Household Burglary". Bureau of Justice Statistics Special Report. [US Department of Justice] September 2010 NCJ227379 Retrieved on 2/24/2021 from <u>https://www.supremecourt.gov/opinions/URLs_Cited/OT2017/15-</u> <u>1498/15-1498-1.pdf</u>

Cohen, L. and Felson, M. (1979) Social Change and Crime Rate Trends: A Routine Activity Approach. American Sociological Review, 44(4): 588-608.

Conte, M. (2019) A closer look at Jersey City's crackdown on Airbnb and other short-term rentals. The Jersey Journal [Jersey City], 25 April 2019, [Digital Article]. Retrieved on 4/18/2020 from https://www.nj.com/hudson/2019/04/a-closer-look-at-jersey-citys-crackdown-on-airbnb-and-other-short-term-rentals.html

Costello, D. (2018). Louisville is proposing a 600-foot rule for Airbnbs: Compromise or catastrophe? The Courier Journal [Louisville], 23 April 2019, [Digital Article]. Retrieved on 3/10/2020 from https://www.courier-journal.com/story/news/politics/metro-government/2019/04/23/louisville-airbnbs-citys-proposed-600-foot-rule-good-bad/3492747002/

Dickey, M. (2018) SF fines two landlords \$2.25 million for illegal Airbnb rentals. *TechCrunch*. Retrieved on 4/4/2020 from <u>https://techcrunch.com/2018/11/05/sf-fines-two-landords-2-25-million-for-illegal-airbnb-rentals/</u>

Eck, J, Weisburd, DL. (2015) Crime Places in Crime Theory. *Crime and Place: Crime Prevention Studies*. 4: 1-33. SSRN: <u>https://ssrn.com/abstract=2629856</u>

Farivar, C. (2017) San Francisco, Airbnb settle lawsuit over new short-term rental law. Ars Technica. 02 May 2017 [Digital Article] Retrieved on 4/12/2020 from <u>https://arstechnica.com/tech-policy/2017/05/san-francisco-airbnb-settle-lawsuit-over-new-short-term-rental-law/</u>

Federal Bureau of Investigation (FBI). (2019) 2019.1 *National Incident-Based Reporting System User Manual*. Criminal Justice Information Services Division Uniform Crime Reporting Program. U.S. Department of Justice. pp. 12-19 Retrieved on 5/10/2020 from <u>https://www.fbi.gov/file-repository/ucr/ucr-2019-1-nibrs-user-manual.pdf/view</u>.

Ferre- Sadurni, L. (2019) Airbnb Suffered a Big Defeat in Jersey City. Here's What That Means. The New York Times [New York], 06 November 2019, [Digital Article]. Retrieved on 3/21/2020 from https://www.nytimes.com/2019/11/05/nyregion/airbnb-jersey-city-election-results.html

Feuer, W. (2019) Airbnb suffers setback in Jersey City as residents vote to regulate short-term rentals. CNBC, 06 November 2019, [Digital Article]. Retrieved on 3/21/2020 from https://www.cnbc.com/2019/11/06/airbnb-suffers-setback-in-jersey-city-on-vote-to-regulate-rentals.html

Glowicki, M. (2019) Metro Council approves Airbnb 600-foot rule, other restrictions. The Courier Journal [Louisville], 24 April 2016, [Digital Article]. Retrieved on 3/21/2020 from <u>https://www.courier-journal.com/story/news/politics/metro-government/2019/04/25/louisville-airbnbs-metro-council-approves-new-limits/3576325002/</u>

InsideAirbnb (2019) Inside Airbnb: Jersey City, InsideAirbnb.com Retrieved on 4/18/2020 from <u>http://insideairbnb.com/reports/inside-airbnb-jersey-city.pdf</u>

Johnson, S. (2018) Las Vegas council rule 'a ban in disguise' on short-term rentals. Las Vegas Review Journal [Las Vegas], 05 December 2018, [Digital Article]. Retrieved on 4/18/2020 from <u>https://www.reviewjournal.com/news/politics-and-government/las-vegas/las-vegas-council-rule-a-banin-disguise-on-short-term-rentals-1543624/</u>

Kagan, J (2018) Non-Owner Occupied Defined. Investopedia, 03/02/2018, [Digital Article]. Retrieved on 3/21/2020 from <u>https://www.investopedia.com/terms/n/non-owner_occupied.asp</u>

Laub, J. H., & Sampson, R. (2003). Shared beginnings, divergent lives: Delinquent boys to age 70. Cambridge, MA: Harvard University Press

Lee, D. (2016) How Airbnb Short-Term Rentals Exacerbate Los Angeles's Affordable Housing Crisis: Analysis and Policy Recommendations. Harvard Law & Policy Review 10(1): 230 -253

Morris, S. (2015) Airbnb is Infuriating the Neighbors. Is it Time for New Rules? Los Angeles Weekly January 22, 2015 [Digital Article], <u>https://www.laweekly.com/airbnb-is-infuriating-the-neighbors-is-it-time-for-new-rules/</u>

Oatman-Stanford, H. (2018) Demolishing the California Dream: How San Francisco Planned Its Own Housing Crisis. Collectors Weekly. 21 September 2018 [Digital Article] Retrieved on 4/13/2020 from https://www.collectorsweekly.com/articles/demolishing-the-california-dream/

Otts, C. (2018) Only five homeowners have been fined under Louisville's Airbnb rules. WDRB News October 28, 2018 [Digital Article] Retrieved on 4/9/2020 from <u>https://www.wdrb.com/news/business/sunday-edition-only-five-homeowners-have-been-fined-under-louisville/article_9dff5a17-eeeb-555c-9acb-af496b6912f3.html</u>

Rowan, C. (2020) Competitors for Airbnb: Who's Stealing Market Share from The Industry Giant? Smartbnb, 13 August 2020, [Digital Article], Retrieved on 2/14/2021 from https://www.smartbnb.io/competitors-for-airbnb/

Sackett, C. (2016). "Neighborhoods and Violent Crime". Office of Policy Development and Research. Summer 2016 [Digital Article] Retrieved on 2/16/2021 from <u>https://www.huduser.gov/portal/periodicals/em/summer16/highlight2.html</u> Samann, R. (2015) Short-Term Rentals and L.A.'s Lost Housing. The Los Angeles Alliance for a New Economy (LAANE). p. 2 Retrieved on 3/29/2020 from <u>https://www.laane.org/wp-content/uploads/2015/08/Short-Term_RentalsLAs-Lost_Housing.pdf</u>

Simmons, A. Short-Term Rental Laws in Major U.S. Cities. 2nd Address Research, 5 February 2020, [Digital Article]. Retrieved on 3/21/2020 from <u>https://www.2ndaddress.com/research/short-term-rental-laws/</u>

Stulberg, A. (2016) Airbnb Probably Isn't Driving Rents Up Much, At Least Not Yet. *FiveThirtyEight*. Retrieved on 4/3/2020 from <u>https://fivethirtyeight.com/features/airbnb-probably-isnt-driving-rents-up-much-at-least-not-yet/</u>

Transparent (2020) Airbnb at IPO part III: How meaningful are Airbnb's competitors? Transparent, 16 November 2020, [Digital Article], Retrieved on 2/14/2021 from <u>https://seetransparent.com/blog/2020/11/16/airbnb-at-ipo-part-iii-how-meaningful-are-airbnb-competitors/</u>

Ulmer, J. T., & Steffensmeier, D. J. (2014). The age and crime relationship: Social variation, social explanations. In Beaver, K., Barnes, J.C., and Boutwell, B. [Eds.], *The Nurture Versus Biosocial Debate in Criminology: On the Origins of Criminal Behavior and Criminality* (pp. 377-396). Thousand Oaks, CA: SAGE Publications Inc. https://doi.org/10.4135/9781483349114.n24

Valencia, M. (2019) Airbnb settles suit with Boston over short-term rental limits. The Boston Globe [Boston], 29 August 2019, [Digital Article]. Retrieved on 2/23/2021 from <u>https://www.bostonglobe.com/business/2019/08/29/airbnb-settles-suit-with-boston-over-short-term-rental-</u>

limits/aZorjDCynWdsRTtz5GWIRM/story.htmlhttps://www.bostonglobe.com/business/2019/08/29/airb nb-settles-suit-with-boston-over-short-term-rental-limits/aZorjDCynWdsRTtz5GWIRM/story.html

Wachsmuth, D, Weisler, A. (2018). Airbnb and the Rent Gap: Gentrification Through the Sharing Economy. Environment and Planning A: Economy and Space. 50(6): 1147 - 1170. https://doi.org/10.1177/0308518X18778038.

Xu, Yu-Hua; Kim, Jin-won; and Pennington-Gray, Lori, (2017). "Explore the Spatial Relationship between Airbnb Rental and Crime". Travel and Tourism Research Association: Advancing Tourism Research Globally. Travel and Tourism Research Association International Conference; 2017 June 20-22; Quebec City, Quebec, Canada. pp.1-9. <u>https://scholarworks.umass.edu/ttra/2017/Grad_Student_Workshop/5</u>