Journal of Quantitative Criminology
https://doi.org/10.1007/s10940-024-09587-2

ORIGINAL PAPER

Do Commercial Place Managers Explain Crime Across Places? Yes and NO(PE)

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Accepted: 7 March 2024

Abstract

Objectives Some criminologists of place have argued that property owners and place managers are the key actors exerting guardianship over crime and driving differences in crime across places, giving rise to the "Neighborhoods Out of Places Explanation" (NOPE) theory of crime. However, research to date has yet to fully evaluate if crime statistically varies across properties, their owners, or surrounding geographies.

Methods Data scraped from Yelp.com is used to identify 1070 land parcels that had at least one business receiving reviews from 2014 to 2020. 911 dispatches for disturbances are linked to parcels and measured as the rate of events per Yelp reviewer in the average year. Hierarchical negative binomial modeling-based variance decomposition techniques are used to evaluate how variation in disturbance rates is distributed across parcels, owners, census blocks, and census tracts. Hierarchical negative binomial models are used to assess the correlates of disturbance rates. Sensitivity analyses assess the correlates of disturbance rates using a single-level negative binomial model with bootstrapped standard errors as well as an alternative outcome measure based on count of 911 events.

Results Commercial disturbance rates vary across parcels, parcel owners, and blocks. At the parcel level, higher Yelp ratings are associated with lower disturbance rates while parcel square footage and land value are associated with increased disturbance rates. Additionally, parcel-level crime disturbance rates are explained by block features such as poverty, violent crime, and the number of Yelp restaurants on the block.

Conclusions Parcel, owner, and block features can all help explain why some restaurants have more crime than others. Future research should build on the place management perspective by investigating the wider breadth of potential actors who may exert guardianship over properties while acknowledging that offenders and targets systematically vary across geographies, making effective guardianship more difficult in some locations than others.

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Published online: 30 March 2024

Keywords Place managers · Neighborhoods · Commercial crime · Restaurants · Yelp

Introduction

The place management perspective emphasizes the role that property and business owners play in controlling crime at the addresses for which they are responsible (Eck 2015; Eck and Madensen 2018; Eck and Clarke 2019; Linning et al. 2022). By maintaining their space, controlling who enters it, and monitoring the activities that occur within, place managers can minimize the amount of crime that occurs (Linning et al. 2022; Madensen 2007). While much of the published literature about place managers is theoretical in nature (see: Linning and Eck 2021; Linning et al. 2022), one recent study demonstrated that accounting for land ownership helps explain crime differences within addresses belonging to the same land use (Lee et al. 2021).

This strong emphasis on the place manager as the key theoretical actor has coincided with a broader shift away from the larger neighborhood geographies used in the earliest studies of crime and place (see: Shaw and McKay 1969) to micro-spatial units representing buildings and addresses. Scholars have observed that a small number of parcels and street segments account for large proportions of urban crime (Sherman et al. 1989) and can explain city-level crime changes (Braga et al. 2011; Weisburd et al. 2004). Crime has shown to be persistent at these micro-locations (Curman et al. 2015; Groff et al. 2010; O'Brien and Winship 2017), making them an increasingly attractive target for policy interventions (LISC 2015; Way 2013).

To theorize about why certain micro-places persistently experience heightened levels of crime, Linning et al. (2022) have recently proposed a "Neighborhoods Out of Places Explanation" (NOPE) theory of crime that argues neighborhood crime differences can be explained by differences in place managers. According to the perspective, parcels will experience different levels of crime depending on the guardianship behaviors of their place managers. These differences between addresses then are expected to aggregate to explain crime differences between larger geographies such as neighborhoods.

NOPE explicitly dismisses the notion that features of communities and larger geographies are relevant to understanding spatial differences in crime (Linning et al. 2022). This perspective is at odds with the other theories of crime and place preceding NOPE. According to routine activities (Cohen and Felson 1979; Felson and Cohen 1980) and crime pattern theories (Brantingham and Brantingham 1995, 2013), social features of places can help us understand the distribution of guardians, offenders, and targets across cities. In a second perspective, social disorganization theory argues that neighborhood demographics dictate how likely residents of a neighborhood are to take action in response to crime (Sampson et al. 1997; Shaw and McKay 1969). If features of blocks and neighborhoods can create differences in the presence of offenders, targets, and guardians across urban locations, we may wonder if parcels vary in their presence of offenders and targets given their location. In this case, it may be easier or more difficult for place managers to control crime in some locations, which would suggest we need to account for geographic characteristics to fully understand spatial differences in crime. However, past research has yet to simultaneously assess the roles of place managers and larger geographies in shaping crime differences across parcels.

This study seeks to clarify the tension about the role of place managers in controlling crime in relation to the surrounding geographies of where places are located. By identifying businesses and linking them to features of their owners and to characteristics of the area surrounding where they are located, we can begin to disaggregate how ownership and geography operate together to create parcel-level crime differences. This can provide us new insight into how place management strategies and the contextual features of larger geographies explain crime differences across places. While past research has generally relied on official data to measure features across parcels, there are additional datasets capturing this information that have yet to be tapped into by criminologists.

To that end, this study draws from a novel dataset of restaurants collected from Yelp, a business review website. Because this dataset includes user reviews and ratings, it is possible to extract substantive information about the activities occurring inside commercial parcels. By counting these reviews, it is also possible to measure how frequently different restaurants get visited. These contextual features provide a new vantage point to investigate why some commercial places experience more crime than others. The study proceeds by reviewing the past theories of crime and place research and NOPE to consider their overlap and tensions.

Literature Review

Traditional Theories of Crime and Place

The vast majority of research on crime and places is rooted in one of several theories. One of these theories, routine activities theory, posits that crime occurs when a motivated offender meets a suitable target in a context where there is no capable guardian present (Cohen and Felson 1979; Felson and Cohen 1980). When applied to specific urban locations, this suggests that crime is most likely to occur in locations that have high presences of offenders and targets and low presences of capable guardians. Notably, routine activities theory is flexible across analytic scales. In one of the original studies, Felson and Cohen (1980) show that large-scale social processes that altered routine activities help explain national robbery trends through the 1950s and 1960s. More recently, studies at smaller geographic scales have shown that routine activities theory is helpful for identifying micro-place features that correlate with crime. For example, one body of research on land use has shown that differences in quantities of protective and risky facilities across micro-geographies such as blocks can explain crime differences (Bernasco and Block 2011; Haberman and Ratcliffe 2015).

An auxiliary theory, crime pattern theory, argues that the distribution of these guardians, offenders, and targets are determined by the large scale day-to-day urban mobility flows that occur as people engage in their routine activities (Brantingham and Brantingham 1995, 2013). To analyze the distribution of these actors, researchers have generated measures of ambient population that represent the number of people present in a given geography. Studies have found that ambient population size effectively explains crime variation across neighborhoods (Andresen 2006, 2011) and at smaller scales, such as blocks (Andresen 2011; Hipp et al. 2019).

Social disorganization theory, a third perspective, positions guardianship activities as a neighborhood-level phenomenon. Proposed in the early twentieth century, social disorganization theory argues that certain demographic factors, including poverty, residential instability, and racial heterogeneity, impede the ability of a neighborhood's residents to come together to take actions that can help prevent crime (Shaw and McKay 1969). More recently, Sampson et al. (1997) showed that a neighborhood measure called collective efficacy representing trust and expectations of shared control within members of a community explains why disadvantaged urban neighborhoods experience more crime than others. There are also allied theories on how social isolation and poverty can motivate or otherwise elicit offending (Peterson and Krivo 2010; Wilson 2012). These perspectives have spurred a massive body of literature demonstrating that neighborhoods, often measured through census tracts, systematically vary in rates of crime and disorder according to their composite demographics and social dynamics (see: Browning 2002; Hipp and Wo 2015; Maimon et al. 2010; Morenoff et al. 2001). While social disorganization theory was formulated as a neighborhood-level theory, studies have also shown that its key variables operate similarly at the micro-scale (Dinesen and Sønderskov 2015; Weisburd et al. 2020), suggesting it can be applied to explain the association between demographic features and crime at smaller geographic scales in addition to tracts.

While routine activities and social disorganization theories are often treated as competing perspectives, both offer that features of places can help explain how many guardians, targets, and offenders are present in a location. According to routine activities and crime pattern theories, measuring the routine activities and land use of places can help explain the locations of guardians, offenders, and targets. Similarly, social disorganization theory argues that demographics can explain how likely residents are to engage in collective guardianship and, in turn, limit criminal behavior, a relationship that could be relevant for neighborhoods as well as more localized scales. However, a new framework building on routine activities theory rejects the role of larger geographies in favor of micro-places and their managers.

Place Managers and Crime

The place management perspective is rooted in the empirical observation that crime meaningfully concentrates across places at very small scales (Eck et al. 2007). Beginning in the late 1980's, criminological studies started to show that crime varies across micro-places even in the same neighborhood (Sherman et al. 1989; Spelman and Eck 1989). Sherman et al. (1989) observed that 3% of parcels accounted for 50% of crimes in Minneapolis, suggesting crime was highly concentrated in a small proportion of "problem properties". Further research has shown that crime rates at micro-places can help explain crime rates for entire cities because the majority of crime is so highly concentrated across a small minority of places (Braga et al. 2011; Weisburd et al. 2004). Even within addresses hosting the same type of land use, studies have found that crime is highly concentrated to a small number of places (Madensen and Eck 2008; Wilcox and Eck 2011). Studies on repeat victimization have shown that certain properties are repeatedly targeted for crimes such as robbery (Farrell and Pease 2001; Johnson et al. 2007). Likewise, recent work has revealed typologies of problem properties with different types of crime and distinct longitudinal trajectories (O'Brien et al. 2022a, 2022b).

The body of work to date has led to a question: why do certain addresses have substantially more crime than others? One answer to this question has looked to the role that place managers or property owners play in shaping crime rates across places. Proposed by Eck (1994), the term "place manager" specifically refers to people who are responsible for overseeing a place or area. According to the place management perspective, it is solely the actions of these individuals that determine how much crime happens in a place. In their official capacity, either via employment or ownership, place managers act to organize the space they manage, control access to that space, and regulate conduct within that space (Madensen 2007). In conducting these duties, place managers will be confronted with situations that force them to make decisions and take actions that either increase or reduce the degree to which potential offenders gravitate toward that place due to perceived criminal opportunity.

A handful of studies have produced evidence suggesting that property owners can control crime through place management practices (Eck and Madensen 2018). Eck (2002) identified five separate experiments that investigated whether owners of problem apartment buildings would be motivated by civil sanctions to control drug crimes happening on their properties. Results from all studies suggested this intervention was effective, providing evidence that manipulation of place management practices changes rates of crime occurrence. More recently, an experimental study found that crime reports were reduced at motels through various outreach and code enforcement strategies that intervened on property owners to enhance place management (Bichler et al. 2013), while a second study showed crime reductions after property owners were fined for excessive calls to police at their property (Payne 2017). In the most recent and cutting-edge assessment of the relationship between place management and crime, Lee et al. (2021) utilized a multivariate modeling strategy and found that clustering addresses within their owners rendered relationships between land use categories and crime statistically insignificant, suggesting that place managers are crucial to understanding crime differences across micro-places.

Formalizing the ideas from this literature, Linning et al. (2022) have proposed a "Neighborhoods Out of Places Explanation" (NOPE) for crime, where differences across neighborhoods can be explained by place manager features. While most place managers are expected to be able to adequately control crime, the theory argues that a small minority of place managers fail to do so, and we can explain the locations where crime occur by identifying the locations operated by these problematic place managers. Not only are place management practices expected to explain crime differences across parcels, but they are also expected to aggregate so that they explain crime differences at larger scales. Under this perspective, any streets or neighborhoods that experience high amounts of crime would be expected to have a high proportion of poor place managers. This association is expected to be so strong that geographic features of cities are not relevant to understanding where crime occurs after accounting for place management features. However, considering this theorized relationship has yet to be formally tested, one might wonder if some place managers operating in criminally vulnerable areas may be overwhelmed by offenders or targets regardless of their aptitude for crime control. In this case, place managers and features of the geographic contexts in which they operate would need to be evaluated in conjunction to fully understand crime variation across micro-places. This possibility is the focus of the current study.

Current Study

While initial research has shown that the identity of the property owner helps account for differences in crime between properties with the same land use (Lee et al. 2021), to our knowledge there has been no empirical test of whether differences between owners are explained by geographic features of the locations where they own property. This represents a major limitation in the literature, as routine activities and crime pattern theories give us ample reason to believe that the crime management of specific buildings may vary across larger geographies. Routine activities theory suggests that guardians will fail to prevent crime if they are overwhelmed by targets and motivated offenders. Thus, we might consider that place managers have a harder time doing their jobs in areas with heightened levels of offenders and targets. Indeed, Madensen and Eck (2013) suggested that property management strategies may need to be more robust in high crime neighborhoods to be effective. As such, one property or business owner might have varied capacity to exert crime control across the multiple parcels they manage across a city. If a place manager's ability to control crime varied across parcels due to their location, it seems it would be crucial to consider geographic features beyond place managers to fully understand which urban locations are most likely to experience crime.

Here we pursue two main questions that need to be tested to fully assess the previously reviewed assumptions of NOPE.[1] First, we test whether quality in place management meaningfully varies across property owners rather than geographies. Second, we formally evaluate if place management features aggregate to explain differences in crime across geographies. To test these questions, the present study uses a novel dataset of restaurant locations and reviews derived from Yelp, a business review website. These data are particularly advantageous for investigating place management mechanisms because (1) they include measures of how customers rated restaurants, providing a proxy measure of general management quality; and (2) they count the number of reviews each business receives, offering a proxy measure of business visitation. This makes our contribution unique in two regards. By measuring business visitation, this study is the first to evaluate place management effects on crime while controlling for volume of micro-place visitation. By measuring these features across businesses, their property owners, and the larger geographies where they are located and comparing them to crime, we can assess the extent to which place managers or geographic context each explain the locations where crime occurs.

Methods

Yelp Data

To measure restaurant locations and visitation, we draw from restaurant reviews posted on Yelp.com made available via the Boston Area Research Initiative's COVID in Boston Database (Ristea et al. 2022). Yelp is a website that allows users to create a profile and share their reviews of commercial establishments. In the Spring of 2020, a Python script was used to scrape restaurant reviews for all restaurants in Boston. To ensure that all restaurants were captured, individual queries were run under the restaurant section of Yelp for each zip-code in Boston. This produced a list of 2664 restaurants. Meta-data were then scraped for each restaurant, and text and meta-data were collected from all posted reviews. This produced a collection of 320,632 online reviews posted about Boston restaurants between 2014 and 2020. Because Yelp reviewers are required to make a profile to post on the site, each review is linked to a unique ID for the person who posted it.

To geolocate each restaurant, addresses listed on Yelp were geocoded to produce GPS coordinates that were then spatially joined to a shapefile of Boston land parcels provided by the geographic infrastructure component of the COVID in Boston database (Ristea et al.

[1] Linning et al. (2022) also assert that property owners create urban structure rather than residents and that residents are not responsible for guardianship behavior, assumptions that are not tested in the present study.

2022; Zoorob et al. 2021). This process identified 1589 parcels with at least one restaurant on Yelp that received a review between 2014 and 2020. In addition to identifying the specific building where each restaurant is located, the geographic infrastructure allows us to see which census block and tract each restaurant falls in. Because many restaurants and bars are located in buildings that have multiple units within them, it was necessary to compose a strategy to link each Yelp business to the most likely unit. To accomplish this, the Tax Assessment land use database was first reduced to only include parcels identified as belonging to the commercial or mixed-use land categories. For the majority of parcels with an associated Yelp business, there was only one unit with the mixed or commercial designation (89.36%). For another 169 parcels represented on Yelp there were multiple mixed use or commercial land uses, making it impossible to identify the relevant unit for inclusion in the analytic sample. For 1420 parcels where units could reliably be linked to Yelp businesses, unit owners listed in the 2018 Tax Database were linked to the Yelp businesses that operated at that parcel.[2] After limiting the data to parcels for which all external datasets could be reliably joined (see below), the study proceeded with a sample of 1070 parcels distributed across 1012 owners, 659 blocks, and 139 tracts.

Ethical Considerations

The IRB at the authors' home institution deemed Yelp data collection to be exempt from review because all information is publicly accessible and personally unidentifiable. However, it is notable that web scraping involves retrieving data from commercial entities without permission. Scholars have argued that engaging in web scraping is crucial for pushing science forward and creating social good (Bruns 2019; Freelon 2018; Venturini and Rogers 2019) and that violating Terms of Service through online data collection is not inherently unethical (Fiesler et al. 2020). Prompted by the Cambridge Analytica scandal in 2018, social media companies have greatly reduced access to data through their sanctioned tools, bringing us into what has been referred to as an "APIcalypse" or "post-API age" where companies solely support research projects that align with corporate goals (Bruns 2019; Freelon 2018). More recently, major platforms such as Twitter (WIRED 2023) and Reddit (Forbes 2023) have recently made moves to drastically reduce API access even further, so web scraping will be increasingly necessary for scientists studying online spaces. Moreover, the United Nations recognizes the right to research as a human right with higher priority than commercial interests (Bruns 2019; United Nations 1966). We minimized the impact of data collection by setting timers so as to not overwhelm Yelp servers beyond normal usage and we analyze reviews in aggregate to protect the privacy of users.

Criminal Disturbances as Evidence of Commercial Place Management

To assess how place management varies across commercial locations, this study focuses on the crimes that are most likely to be produced through the routine activities occurring at restaurants and bars. Alcohol sales and consumption may lead to heightened levels of social disorder as self-control is diminished among the consumer base. Concerts or other social events held at restaurants and bars may also create heightened emotions that lead to criminal offending. Notably, these activities can frequently occur without crimes being

[2] For the purpose of multi-level modeling, owners have been assigned unique numeric identifiers in order to cluster properties that have the same owner according to the Property Assessment database.

committed. As such, commercial locations that systematically experience crimes arising from minor social disturbances are micro-places that are most likely to have inefficient place managers.

This study measures criminal disturbances using 911 dispatch data from 2014 to 2020 provided by the Boston Police Department. Dispatch data includes a tag indicating the type of criminal event that prompted each dispatch. The dispatch data include 8 sub-categories of labels under the disturbance tag: *alcohol*, *gang*, *music*, *noise*, *panhandling*, *party*, *verbal*, and *default*. An additional type of dispatch, *"IVPER"* indicates a person needed to be removed from a commercial business. Counts of each category of dispatch have been summed to create a singular measure representing commercial disturbances (See Appendix A for more information of measurement validation).

The dispatch data also includes a set of GPS coordinates indicating the exact location of the event. Locations were spatial joined to the land parcel shapefile to identify in which building each event occurred. A within-polygon spatial join was used so disturbances are only associated with a building if the dispatch was made exactly to the building. While this strategy is conservative and may miss commercial disturbances that spill into the public, it serves to isolate the analyzed crimes from crimes that may be produced through external mechanisms. To further isolate disturbances occurring at operating commercial businesses, the dispatch data was limited to only dispatches that occurred at parcels with identified Yelp businesses in years where a Yelp business located at that parcel received at least one review. Following this screening process there were 21,682 disturbance dispatches to the analyzed parcels. While the sample of analyzed parcels only accounts for 1.08% of all parcels in Boston, these parcels generated 7.30% of all disturbance dispatches in the city, suggesting that disturbance dispatches concentrate disproportionately at the types of commercial restaurant spaces represented on Yelp.

Accounting for Differences in Commercial Visitation

Given that crime at a commercial business is likely to be strongly driven by how many visitors it has, studies on commercial place management are limited when they cannot account for this land use characteristic (see: Lee et al. 2021). To address this limitation, the present study measures commercial disturbances by frequency of reviews as a proxy for visitation rate. Because a single parcel could have multiple Yelp businesses operating there over time or even simultaneously, review frequency at each parcel is measured as the total number of reviews received by all Yelp businesses geolocated there between 2014 and 2020.[3] Because not all parcels had businesses operating for the same number of years, the review frequency of each parcel was divided by the number of years at least one business received a Yelp review at the parcel to measure the average number of reviews each parcel received per year of Yelp business operation.[4] To address the possibility that one user could potentially post many reviews for a single restaurant, the data was reduced so each user only counted once per year. Following this process, the average parcel in the analytic sample received 55.20 reviews per year.

Disturbance dispatches occurring at parcels in years where a Yelp business was operating were summed and divided by the number of years a Yelp business operated there to

[3] Reviews posted prior to 2014 were excluded.

[4] Parcels receiving less than 5 reviews in the average year of operation were removed from the analytic sample.

calculate the average number of disturbances per year. The disturbance per analyzed year measures were then divided by the average number of reviewers per analyzed year to calculate final measures of disturbances per Yelp review in the average year a Yelp business was in operation.

Ratings as an Indicator of Management Quality

Outside of disturbances, one additional variable represented on Yelp may serve as a proxy measure of management quality. Madensen and Eck (2008) suggest that place managers who effectively control crime are able to do so because they operate well-functioning businesses more broadly. As such, measures of business quality are theoretically expected to correlate strongly with place managers' ability to deter crime. When Yelp users review a restaurant, they are prompted to rate the quality from 1 to 5 stars. Ratings are averaged within restaurants and then averaged within parcels (where there are multiple businesses in a single parcel) to create a *ratings* variable.

Parcel-Level Controls

Additionally, several variables are created from the Boston Tax Assessment land parcel database. A *mixed land use* dummy variable has been created that indicates whether a parcel is mixed use or strictly commercial. *Land value* is a variable in dollars representing to total assessed value of a parcel. *Square footage* is the area of the parcel.

Measuring Geographic Features

Beyond considering the nature of commercial parcels and parcel owners, this study also considers how commercial micro-places are impacted by the geographies surrounding them. As such, several additional external datasets are used to create census block-level measures.

Routine Activities of Contextual Geographies

Data generated from geotagged Twitter posts were used to generate a block-level measure of ambient population size. Past research has shown that geotagged 'tweets' effectively capture urban mobility patterns (Gao et al. 2014; Lenormand et al. 2014; Phillips et al. 2019; Wang et al. 2018) and have utility for explaining micro-spatial variation in crime (Hipp et al. 2019; Tucker et al. 2021). Tweets were collected via Twitter's Streaming API, a tool that allows analysts to download information on up to 1% of tweets globally. For Twitter users who opt-in, meta-data includes a timestamp and GPS coordinates of the location from which the tweet was posted online, allowing users to be located in space at the time of their tweet. Using this information, the sample of global tweets was reduced to tweets geolocated in Boston posted from 2016 to 2018 to create an analytic sample for the current study. To aggregate tweets to create block-level measures of ambient population size, the data were reduced to one tweet per-user per-block per-week and then aggregated on block ID to count how many users were geolocated in each block for each week in the period of interest.[5] Ambient population sizes were then averaged across weeks to calculate the ambient population size of each block in the average week. The average analyzed block had 62.08 unique Twitter users present in 2018, with the most frequented blocks having thousands.

Beyond counts of people, the number of commercial establishments on each block may also shape the proportional representation of guardians, targets, and offenders in the surrounding area. The number of analyzed Yelp businesses operating on each block has been counted to generate a proxy-measure of commercial activity.

Residential Demographics

The research design also accounts for the residential demographics of the area where each commercial business is located using information provided by the census. The percentage of Black residents is measured using data from the 2010 Decennial Census.[6] The percentage of families in poverty is measured by imputing the block's families in poverty from the 2014 to 2018 American Community Survey's (ACS) block group-level estimates of families in poverty[7]; the use of the ACS is necessary because the Decennial Census does not publish block-level poverty information for all blocks.

Criminal Context

Finally, the study includes several block-level measures of crime to evaluate the interplay between commercial disturbances and crime in the surrounding area. Following the approach of past research (O'Brien and Sampson 2015), 911 dispatch data has been used to generate measures of *violence, gun crime,* and *private conflict*. For each type of dispatch, block-level annual dispatch counts were averaged from 2014 to 2020 to generate the measures for the present study.

Analytic Strategy

The assessment of these data proceeds in two main steps to consider geographic variations and relationships of commercial disturbances.

At Which Scales do Commercial Disturbances Vary?

First, a multilevel modeling variance decomposition strategy is used to assess at which scales there is meaningful variation in commercial disturbance. By assessing whether variation in commercial disturbances is predominantly across owner or geographic IDs, it can be assessed whether commercial disturbances are produced through ownership phenomena or via contextual effects of the surrounding area. The analytic scales for this exercise have been selected according to the scales emphasized by past crime and place research.

[5] We measure ambient population as a weekly average because measures at smaller temporal scales such as day or hours are unstable at the census block geographic scale due to data sparsity.

[6] For 253 blocks that lacked enough residents to report demographics in the decennial census, percent Black was imputed from the block group via the 2014–2018 American Community Survey.

[7] This strategy assumes that median income is uniformly distributed across blocks within a tract.

Considering that social disorganization research has generally studied *tracts* (Sampson et al. 1997; Sampson and Bartusch 1998; Sampson 2006), routine activities theory studies have frequently evaluated *blocks* (Bernasco and Block 2011; Haberman and Ratcliffe 2015; Hipp et al. 2019), and the place management perspective emphasizes *parcels* and their *owners* (Lee et al. 2021; Linning et al. 2022), these four scales have been selected for the present analysis.

Multilevel Modeling Strategy

Each parcel in the analytic sample has been linked to the ID of its owner as well as the geographic identifiers of the Census block and tract in which it is located. By calculating a null hierarchical negative binomial regression model where variance is partitioned across these analytic levels, it is possible to assess at which scale the variation occurs (see: Raudenbush and Bryk 2002). Because owners can potentially have properties on multiple blocks, to implement this strategy on the present data, parcels (n = 1070) have been cross classified by owners (n = 1012) and blocks (n = 659). Blocks are then nested within tracts (n = 139) to create a 4-level structure that connects parcels with Yelp businesses to their owners and geographic locations. Using random intercept models with no independent variables, rates of disturbance per review are regressed with a structure defined as (Greene 2007):

T_{ijk} = parcels in owner.

N_{ij} = Owners within blocks.

M_i = blocks within tracts.

L = tracts.

$y_{i(jk)t}$ = disturbance rate for parcel t, owner k, block j, tract i

Using the following equation:

$$y_{i(jk)t} = \boldsymbol{X'}_{\boldsymbol{i(jk)t}}\boldsymbol{\beta} + \boldsymbol{u}_{\boldsymbol{i(jk)}} + \boldsymbol{v}_{\boldsymbol{ij}} + \boldsymbol{w}_{\boldsymbol{i}} + \boldsymbol{\varepsilon}_{\boldsymbol{i(jk)t}}$$

where: X' = Independent predictors; u = Owner-level error term; v = Block-level error term; w = Tract-level error term; ε = Parcel-level error term.

Visual examination of the disturbance rate variable suggested a strongly positively skewed distribution. Because this distribution is often analyzed through negative binomial models, study models are estimated with a negative binomial specification.[8]

Assessment of variance components can then provide evidence about whether these forms of commercial disturbance are rooted in geographic or place management processes. If property owners represent place managers whose behaviors completely explain crime differences across all urban scales as proposed by NOPE, the results would show that a large proportion of variation is attributed to property owners (see Appendix B for additional information about variance decomposition strategy).

Data Sparsity

Given the nested structure of the analysis, it is crucial to consider whether there is enough data available across scales to support multilevel modeling. There is relatively strong

[8] Notably, some previous studies analyzing crime rates through negative binomial models have used an exposure variable approach where the natural log of the population at risk is included as a model parameter (see: Osgood 2000). The present study also considers this approach in secondary analyses to evaluate the robustness of results (See Results section for additional information).

Table 1 Average sample size per nested level of analysis

	Avg. per tract (std)	Avg. per block (std)	Avg. per owner (std)
Block	4.74 (6.37)		1.03 (0.20)
Owner	7.40 (11.72)	1.58 (1.22)	
Parcel	7.70 (12.37)	1.62 (1.32)	1.06 (0.28)

representation across census tracts, with the average tract linked to 7.70 parcels, 7.40 owners, and 4.74 blocks (see Table 1). However, data is sparse across parcels, owners, and blocks. The average block is linked to 1.62 parcels and 1.58 owners while the average owner is associated with just 1.06 parcels and 1.03 blocks.

While these figures represent very low variation that may limit the utility of multi-level models, it seems this sparseness captures an important feature of property ownership phenomena; across all commercial or mixed-use property owners in Boston, the average owner has 1.41 commercial or mixed-use properties and the median owner has properties on just two blocks. A recent study of property owners in Cincinnati also found that properties are overwhelmingly owned by single-property owners (see: Lee et al. 2021).

Despite this data sparseness, multilevel modeling is, to our knowledge, the only statistical methodology that allows us to distribute variance across nested levels. Evaluating the degree of variance in commercial disturbances at each analytic level allows us to test the NOPE argument that crime is explained by place management features rather than geographic context. While this modeling strategy may overstate the proportion of variance attributed to parcels and property owners given the data sparseness and structure of crime data (Bernasco and Steenbeek 2017; O'Brien 2019), it remains the most appropriate technique to answer the central question of this study.

What are the Correlates of Commercial Disturbance?

The aforementioned variance decomposition exercise will identify analytic scales where statistically significant predictors of commercial disturbance are most likely to operate. For example, if the variance decomposition results suggest that social disturbances primarily vary across owners and census blocks, it would suggest that features of owners and blocks are those that will primarily explain variation in social disturbances. As such, multi-level models are conducted at the scales deemed relevant by the variance decomposition results to assess which features are associated with commercial disturbance.

Results

Variation in Commercial Disturbances

Descriptive statistics suggest that there is substantial variation in disturbance rates across parcels (See Table 2). While the typical parcel had 0.17 disturbance dispatches per Yelp reviewer in the average year, some had as many as 10.23. The average parcel had an average Yelp rating of 3.63, with the distribution of rating scores being roughly normally distributed around this central value of the rating scale. Block-level descriptive statistics are also presented to get a sense of the geographic context where each parcel is located

Table 2 Descriptive Statistics for Parcel-Level Variables

	Parcels (N = 1070)	
	N (%)/Mean (SD)	Range
Disturbance rate	0.17 (0.63)	0.00–10.23
Avg. Yelp rating	3.63 (0.59)	1.00–5.00
Mixed use	358 (33.46%)	
Land value	19,321,183.98 (67,561,028.11)	28,300–855,195,500.00
Square footage	18,212.45 (57,490.63)	265.00–823, 572.00

Table 3 Block-level descriptive stats (n = 659 blocks)

	N(%)/Mean (SD)	Range
Avg. ambient population	2.03 (15.28)	0.02–352.79
Yelp count	1.62 (1.32)	1.00–13.00
Families in poverty	0.10 (0.11)	0.00–0.46
Proportion black	0.10 (0.15)	0.00–0.82
Gun crime	0.47 (0.78)	0.00–8.36
Violence	5.77 (8.36)	0.00–71.91
Private conflict	1.54 (1.45)	0.00–18.81

Table 4 HLM derived variance proportions in commercial disturbances per Yelp review (*n* = 1,070 parcels, 1,012 owners, 659 blocks, 139 tracts)

	Marginal variance component (% of total variance)
Parcel	0.165 (63.57%)
Owner	0.068 (26.40%)
Block	0.024 (9.36%)
Tract	0.001 (0.68%)

(See Table 3). The average analyzed block has 1.62 parcels with a Yelp business on it, with some having as many as 13. Analyzed blocks also vary greatly in terms of crime and demographics.

A hierarchical negative binomial model without independent variables was used to assess the scale at which the commercial disturbances vary (See Table 4). This exercise allowed us to compare scales to evaluate at which level features explain the most variation in our outcome of interest. Variance components suggested that disturbances primarily vary across parcels (63.57%). Additionally, there were meaningful amounts of variance attributed to owners (26.40%) and blocks (9.36%), yet almost none attributed to tracts (0.68%). This indicated that parcel features are most central to explaining variation in commercial disturbances, accounting for a higher proportion of variation than the rest of the levels combined. Additionally, these results suggested owner and block features are also substantially relevant for explaining variation in commercial disturbances across places.

Table 5 Hierarchical Negative Binomial Models Evaluating Correlates of Commercial Disturbance Per Yelp Review ($n = 1{,}070$ parcels, 1,012 owners, 659 blocks)

	Model 1 IRR (std. error)	Model 2 IRR (std. error)	Model 3 IRR (std. error)
Intercept	0.06 (1.19)***	0.07 (1.18)***	0.07 (1.21)***
Parcel features			
Mixed use		0.78 (1.22)	0.89 (1.26)
Avg. land value		1.15 (1.06)*	1.15 (1.06)*
Avg. square footage		1.16 (1.05)**	1.17 (1.05)***
Avg. Yelp rating		0.62 (1.08)***	0.56 (1.13)***
Block features			
Ambient population	0.98 (1.12)	0.89 (1.17)	0.91 (1.19)
Yelp count	0.73 (1.13)*	0.77 (1.13)*	0.63 (1.17)**
Gun crime	1.18 (1.13)	1.24 (1.11)*	1.30 (1.12)*
Violent crime	1.62 (1.10)***	1.49 (1.08)***	1.47 (1.10)***
Private conflict	0.86 (1.12)	0.86 (1.11)	0.83 (1.11)
Families in poverty	4.18 (2.34)	5.73 (2.02)*	7.76 (2.34)*
Percent black	2.17 (2.05)	0.93 (1.77)	1.06 (2.00)
Interactions			
Ratings * Yelp count			0.81 (1.10)*
Ratings * Guns			1.03 (1.06)
Ratings * Violence			0.99 (1.06)
Ratings * Poverty			1.77 (2.03)
Marginal block variance	0.00216	0.00101	0.00243
Marginal owner variance	0.01317	0.00426	0.00000
Marginal parcel variance	0.10383	0.09254	0.08104

To aid in the interpretation of effect sizes, parameters were grand-mean centered and standardized (z-scores) prior to analysis

Assessing Correlates of Commercial Disturbance

Next, the study proceeded to assess the correlates of the commercial disturbance measures by estimating multi-level models at the relevant scales identified in the variance decomposition exercise. Because the variance decomposition results suggest that accounting for the hierarchical structure accounts for all variation in commercial disturbances across tracts, there is no reason to believe that variables at that scale will have statistically significant associations to disturbances when other levels are accounted for. To maximize the degrees of freedom available in the model while also capturing all analytic scales of import, the study limits the rest of analyses to only scales with substantial variation by using a 3-level negative binomial model cross-classifying parcels with owners and blocks.

To begin evaluating the owner- and block-level features that predict commercial social disturbances, the first model began by regressing the parcel-level rate of disturbances on block-level indicators of ambient population size, number of Yelp parcels, crime rates, and residential demographics (See Table 5, Model 1). This model only included block-level indictors provided a baseline of how block features associate with social disturbances before accounting for ownership features. Results indicated that block-level violent crime counts (IRR = 1.61, $p < 0.001$) were positively associated with increased rates of social disturbance at parcels with Yelp businesses, while the count of Yelp restaurants on each block was negatively associated with disturbance rates (IRR = 0.73, $p < 0.05$).

Model 2 further assessed the criminogenic nature of property and owner features while controlling for block characteristics. Results suggested that parcel and block features combine to explain the distribution of disturbances. Parcels hosting businesses with higher average ratings on Yelp (IRR = 0.62, $p < 0.001$) tended to experience lower rates of disturbances, suggesting that place management features are correlated with crime frequency. Additionally, larger parcels (IRR = 1.21, $p < 0.01$) and more valuable parcels (IRR = 1.15, $p < 0.05$) were associated with increased disturbance rates. Moving to the block-level, representing violence (IRR = 1.49, $p < 0.001$) and count of Yelp businesses (IRR = 0.77, $p < 0.05$) still predicted more disturbances even when parcel features were accounted for. Additionally, the inclusion of parcel features caused several block-level variables to gain significance, indicating that parcels with Yelp businesses tend to experience higher rates of criminal disturbance when they are located on blocks with higher rates of poverty (IRR = 5.73, $p < 0.05$) and higher counts of gun crime (IRR = 1.24, $p < 0.05$). Considering that accounting for parcel features also caused a reduction in the block-level and owner-level variance components, all together this suggests some block- and owner-level differences in disturbance rates can be accounted for by systematic differences in the nature of parcels with Yelp businesses.

Given that NOPE argues place management features are central to explaining crime differences across geographies, if place management quality systematically varies across blocks it could explain the high degree of variation in rates of commercial disturbance at that scale. To assess this possibility, we estimated a regression model that allowed parcel-level slopes to vary across blocks while including interaction terms between our proxy-measure of place management, Yelp review scores, and four block-level features that were shown to be correlated with commercial disturbance rates: gun crime, violence, poverty, and count of Yelp businesses (See Table 5, Model 3). Results indicated there was a statistically significant negative interaction between ratings and the number of Yelp businesses on each block (IRR = 0.81, $p < 0.05$). Parcels with low ratings appear to be especially vulnerable to crime when there are fewer parcels with Yelp businesses on their block, while there seem to be protective effects for low-rated parcels on blocks dense with other Yelp businesses (See Fig. 1).

Sensitivity Analyses

Due to the low sample size of parcels across owners, it is possible that multilevel analyses misrepresent the relationship between variables. To consider this possibility we have constructed non-hierarchical negative binomial models with bootstrapped standard errors because this technique addresses the statistical issues that arise when there is not enough statistical power for a multilevel analysis (Krull and MacKinnon 2001) (See: Appendix C). Model 1, which regresses parcel and block features on commercial disturbance rates, generally resembles the hierarchical estimation of the same model; notably, block-level measures representing counts of Yelp restaurants and gun crimes lost statistical significance in the non-hierarchical models. Introducing interaction terms (See: Model 2) caused all block features to lose statistical significance. Moreover, the coefficient representing the interaction between ratings and block-level Yelp count marginally fails to achieve statistical significance (IRR = 0.84, $p = 0.053$). While these non-hierarchical models with interactions

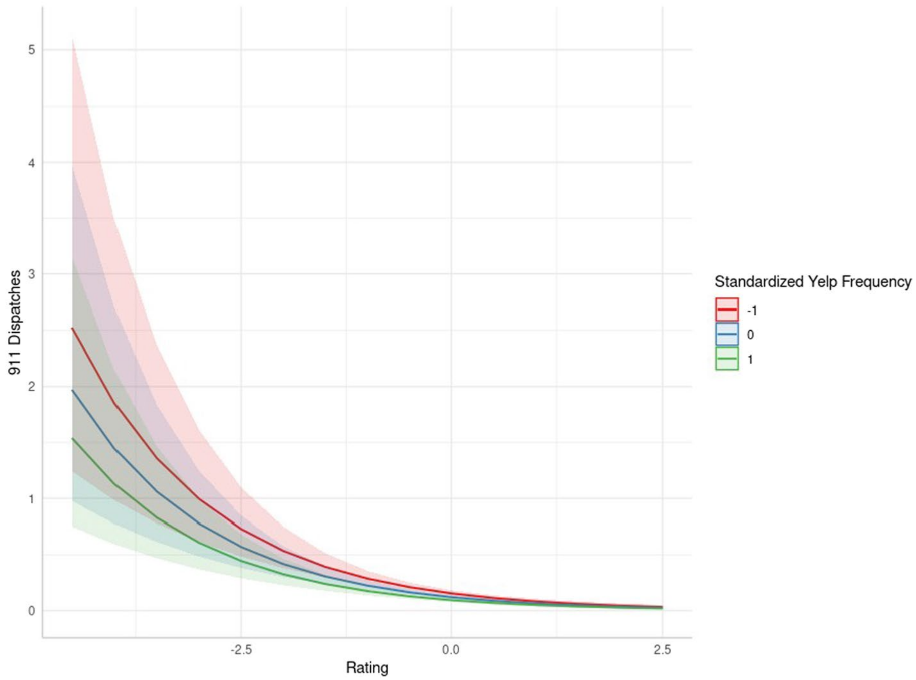

Fig. 1 Interaction between ratings and count of Yelp restaurants on block in predicting crime

substantially diverge from the hierarchical variant, single-level negative binomial models should be less equipped to evaluate cross-level interactions, even with bootstrapped standard errors. Most importantly, baseline models using both the HLM strategy and the single-level bootstrapped standard error method consistently showed that both property-level and block-level features are correlated with crime, bolstering our argument that place manager features alone do not fully explain geographic variation in crime.

Additionally, if certain types of restaurants are more likely to be reviewed than others our outcome measure that calculates crime as a rate per Yelp reviewer may be biased. To evaluate how this methodological choice impacted the analytic results, Appendix D presents alternative models that replace the dependent variable with the raw number of 911 dispatches each parcel experienced in the average year a Yelp business was operating there.[9] Results from models analyzing the count outcome are generally comparable to the rate models. However, there were several key differences: the count models did not find a statistically significant relationship between gun crime and commercial disturbances, nor was there a statistically significant interaction between ratings and block-level count of Yelp businesses.

Overall, the results from sensitivity analyses support our central argument that both parcel features and block characteristics contribute to explaining crime differences across parcels with Yelp businesses.

[9] Past studies have argued that crime rates should be analyzed through negative binomial models using an exposure variable approach (See: Osgood 2000). The log of review counts in the average year was implemented as an exposure variable using the offset option within the glmmTMB R library.

Discussion

A cohort of scholars in crime and place have established a new perspective that property owners and place managers are the main actors enforcing crime management. This perspective has led to the conceptualization of the NOPE theory that posits land parcels experience crime purely as a product of place management practices and deficiencies in place management practices aggregate to explain differences in crime across neighborhoods. To evaluate this theory, this study combined novel datasets generated from online posts and administrative information to construct measures of disturbances per visitation and restaurant rating. By leveraging information listed on Yelp and contextualizing it with geographically informed official data, this study represents a first step in harvesting theoretically relevant information from online postings to understand crime variation across commercial micro-places.

The measures developed through this approach were then investigated in terms of their scales of variation and external correlations. Overall, study findings represent mixed results for the validity of NOPE. While there is substantial variation in commercial disturbances attributed to property owners and very little variation attributed to neighborhood, there is also a notable degree of variation across blocks. Moreover, commercial disturbances were correlated with block-level features when accounting for ownership variation and parcel features, suggesting that place management features alone are not enough to fully explain crime differences across parcels. Finally, we learned that the relationship between our proxy measure of place management and crime depends on the number of restaurants on the surrounding block, implying a multi-level process where place management efficacy is impacted by features of the local social environment.

This set of results provides mixed evidence for NOPE. Indeed, we found support for NOPE's emphasis on the crucial role that place managers play in shaping crime differences across micro-places. Over a quarter of all variation in commercial disturbances was distributed across property owners, accounting for more variation than block and tract features combined. However, other findings contradict NOPE's contention that criminologists can ignore geographic context in favor of evaluating place management processes. Overall, the results from this study suggest that place managers play a major role in determining where crime happens, but their ability to manage micro-places is impacted by the social context of the geographies where they operate. We contend that social disorganization theory and other ecological frameworks remain useful for theorizing about how place managers are impacted by their sociospatial context. Below, we integrate both NOPE and Chicago School theory to interpret several key takeaways from this study in further depth.

Formally Assessing Spatial Variation in Place Management

One of the key arguments of NOPE and the larger place management perspective is that place managers are central actors determining where crime happens. Given that NOPE is non-specific about relevant crimes, variance decomposition analyses of any given crime type should show that crime frequency predominantly varies across owners. While past research has conducted variance decomposition analyses that nest parcels within their owners (Lee et al. 2021), this study represents the first effort to nest parcels within theirs owners and the geographies where they are located. This study attempted to isolate the crimes that were most likely to be produced through place management mechanisms: disturbance dispatches that were sent directly to commercial parcels.

Using this conservative strategy, results suggested that disturbances varied across parcels, owners, *and* blocks. On the one hand, these results align with NOPE's broad argument that neighborhoods are not the central scale that crime should be understood through, a finding that is consistent with other recent research on crime concentration (O'Brien and Ciomek 2022). On the other hand, our study's findings bring into question NOPE's argument that ownership processes are the only mechanisms of crime we should be paying attention to. Instead, the results suggest features of blocks, owners, and parcels can simultaneously enhance our understanding of where crime occurs. Notably, multilevel model-based variance decomposition analyses are vulnerable to overstating variation at lower analytic scales, especially for measures like crime, which feature lots of zeros and ones and a handful of higher values (Bernasco and Steenbeek 2017; O'Brien 2019). Future studies should further consider with factors at larger geographic scales such as neighborhoods or even municipal boundaries shape crimes differences across micro-spatial geographies.

Understanding How Parcel Differences Drive Commercial Disturbance Rates

Findings from this study suggest that features of parcels are correlated with rates of commercial disturbance, with two main parcel features emerging in particular. For one, rates of commercial disturbance appear to be associated with the average ratings businesses in a parcel receive on Yelp. Specifically, each additional star a restaurant receives on Yelp is associated with a 43.8% reduction in commercial disturbance rates.[10] This may suggest the actions business managers take to operate well-received restaurants serve to control crime within that establishment (Madensen and Eck 2008). Note that we do not argue Yelp reviews represent a direct measure of place managers' propensity for crime control; review scores are most likely to be based on perceptions of ambience, food, and service quality rather than beliefs about crime likelihood, and many actions place managers take to control crime may not be observable to patrons. Instead, we argue that review scores broadly capture how effectively place managers run businesses and thus by proxy explain variation in propensity for crime control. This is consistent with the arguments set forth by Madensen and Eck (2008), who highlight that the majority of place managers' efforts are geared towards successfully operating businesses rather than controlling crime. Incidentally, the actions needed to operate profitable businesses tend to overlap with crime control strategies; while the manager of a busy restaurant will likely take measures to encourage front-of-house staff to circulate around the building to attend to patrons, this staff mobility increases surveillance across the space, potentially leading to reduced crime. If boisterous, inebriated bar patrons deter others from visiting, place managers who want to maximize profits should engage in guardianship to minimize drunkenness within the space they control. Given such processes, while Yelp ratings are not a perfect measure of business-level crime control, we contend that ratings are a useful proxy and the strongest generalizable measure of place management proposed by criminologists to date. Future research should further investigate actions that businesses and the individuals representing them take to control crime and design strategies to measure these actions across businesses.

Additionally, larger and higher value land parcels appear to be associated with higher rates of disturbance. This may be explained by systematic differences in routine activities across types of commercial parcels. Larger and higher value parcels may be more likely to hold major events such as concerts and parties. While the present study controlled

[10] Calculated by re-estimating Model 2 from Table 5 using an unstandardized parameter.

for visitation numbers at both the parcel- and block-levels, it is possible such establishments maintain social environments that incite disturbing behavior for reasons unrelated to crowd size; Boston's tourist trap Irish pubs may not experience the same levels of crime as the local night clubs even if both establishments have similar levels of visitation. Future research should consider strategies for measuring social dynamics within commercial spaces to identify new mechanisms linking routine activities to crime differences across parcels.

Relevant Block Features

Poverty & Crime

Results from multilevel models suggested that block-level indicators of poverty and crime are correlated with disturbance rates even when accounting for features of parcels and owners. Specifically, disturbances are correlated with block-level rates of poverty, violent crime, and gun crime. This set of findings has several interpretations. On one hand, it is possible that residential demographics and crime are capturing block-level variance in unmeasured features of micro-places or place managers. It could be possible due to poverty and historical discrimination, neighborhoods with concentrated disadvantage have place managers who face additional personal barriers or lack motivation to control crime. This would be consistent with the NOPE argument that urban micro-places are often managed by 'creators' who may not be present or live in the city (Linning et al. 2022). Future research should evaluate whether low-income blocks facing crime issues are more likely to managed by outsiders, as this could potentially be an interesting mechanism linking block features to place management characteristics. More broadly, further research on the characteristics of place managers, how their behavior changes across contexts, and how they select (or are selected into) certain geographies could serve to explain away block features that appear to correlate with disturbances in the current study.

Alternatively, these results linking residential demographics and violent crime to commercial disturbances can be interpreted through a social disorganization lens. Social disorganization theory argues that residential features such as poverty impede the ability of community members to trust one another and work together to address shared problems, leading to increased crime (Sampson et al. 1997; Shaw and McKay 1969). While the theory has traditionally been conceptualized and tested using neighborhood-level units, there is some evidence that the theory operates at micro-spatial scales such as blocks (Weisburd et al. 2020). Through this framework, we would assume that residents are actors engaging in guardianship, with residents of neighborhoods high in concentrated disadvantage being the least likely to take action to prevent crime. As a result of this reduced social control, such neighborhoods are also expected to be over-represented in terms of motivated offenders (Peterson and Krivo 2010; Wilson 2012). If property managers in economically impoverished neighborhoods operate in areas with higher proportions of offenders and lower proportions of targets this would explain why parcels in such neighborhoods would experience increased rates of disturbance even when accounting for ownership and parcel features. While Linning et al. (2022) propose that NOPE improves upon social disorganization theory by shifting the theoretical guardian role from residents to the place manager, social disorganization theory may still have utility for assessing place management vulnerabilities across geographies.

Furthermore, the connection between block-level features and commercial disturbances could be interpreted through the lens of routine activities and crime pattern theory. Given routine activities theory's proposition that motivated offenders commit crime near places known to them through their daily activities, restaurants on high crime blocks should theoretically have a higher likelihood of being within the activity spaces of offenders. If a high crime block has a reputation among offenders as an advantageous place to offend the motivated offenders attracted to the area may utilize nearby restaurants for either criminal or non-criminal purposes. Incidentally, even if restaurants themselves are not crime attractors, they may be subject to the effects of other attractors in the local area. Future research should develop strategies to measure place management quality across a wider variety of business types to facilitate analysis of spatial spillover effects across place managers.

Business Proliferation

We also found that parcels have lower rates of commercial disturbance when located on blocks with higher numbers of parcels with Yelp businesses. This variable appears to be particularly relevant to understanding how place management processes operate across space, evidenced by a statistically significant interaction with our proxy for place management, Yelp review scores. There are several possible interpretations of this result. On one hand, it is possible that restaurant managers on the same block collaborate and combine resources to fund larger deterrent strategies or garner anti-crime resources from local government. In this event, restaurants on blocks with other restaurants may benefit from enhanced guardianship relative to restaurants in other land use contexts, with low-rated restaurants having the most to potentially gain from shared guardianship. Alternatively, blocks with multiple restaurants may have distinct routine activities that relatively deter crime through mechanisms unrelated to commercial place management. Notably, city blocks with multiple restaurants are typically representative of commercial hubs. If local policymakers are invested in generating economic activity and keeping shoppers safe, blocks with multiple restaurants and other businesses may have increased law enforcement presence. While the results from this study suggest that restaurants with high quality place management can control crime independently, police presence may still be a key asset for poorly managed locations on commercially dense blocks. Conversely, restaurants on blocks surrounded by residences or vacant land are likely to be lower priority for targeted enforcement, making these restaurants vulnerable even when controlling for place management quality. To clarify these possibilities, future research should consider how place managers benefit from adjacent guardianship efforts sustained by police and other businesses.

Limitations

Before concluding, limitations of the present study are considered. This study analyzes parcel-level measures of restaurant visitation and management quality in relation to crime for over 1000 restaurants, representing a relatively robust balance of sample size vs. information depth compared to other studies on this topic. While these restaurants were distributed across Boston's neighborhoods, a relatively small number of blocks are represented. Though this may just be somewhat reflective of concentration in commercial places, it does limit the statistical power of analyses. Additionally, parcels are relatively sparsely distributed across owners and blocks. As such, there may not be enough variation across all analytic scales to be calculating 4-level regressions on a small sample of parcels. However, this is a structural issue rather than a data issue; across all commercial or mixed-use property owners in Boston, the average owner has 1.41 commercial or mixed-use properties (compared to 1.06 in the analytic sample) and the median owner has properties on just two blocks. Future research should consider whether Gini coefficients (O'Brien 2019) or other techniques for analyzing variance across scales would be better suited to evaluate feature variance across commercial property owners. In any case, this may speak more to the empirical testability of the theory itself more than it does to the quality of our data or analytic strategy. Specifically, given that just 4.74% of parcels in the study sample belong to owners with multiple properties, it is unclear whether parcels and their owners should be analytically and theoretically distinguished from one another.

Furthermore, this study essentially only analyzes a single land use. While different varieties of restaurants and bars represented in the Yelp data may have diverse routine activities and place management challenges, they are likely to be much more similar to each other than to other types of land use. In particular, the results from this study may not generalize to residential parcels. The strategies that landlords use to manage crime are likely vastly different from commercial place managers, so future research will need to further investigate how residential place managers operate. Additionally, the amount of crime restaurants experience may be dependent on other businesses operating in the area. For example, a restaurant with a cannabis dispensary next door may be more vulnerable than a restaurant next to a library. Expanding place management evaluation to a wider set of businesses would be valuable for understanding how place managers are impacted by other place managers in their surrounding context. Finally, there may be biases in which restaurants get posted about on Yelp. If certain types of restaurants are systematically under-reviewed on Yelp, the crowd-sourced data could provide a skewed picture of the locations, characteristics, and visitation rates of Boston restaurants.

Additionally, the 911-based dispatch data used to measure commercial disturbances may have biases correlated with place management practices. Specifically, some place managers may utilize alternative strategies where they exert crime control over their parcel without dialing 911. In the context of a restaurant or bar, it would not seem particularly unusual if someone causing a disturbance was asked to leave or even forcibly removed. On one hand, this does seem to represent place management behavior that would reduce crime at the parcel. On the other, it seems that strategies alternative to police reporting could potentially have dispersion effects where unruly individuals leave that bar and later commit crime in another nearby location. For example, in July of 2021 one owner of a restaurant represented in the study data attended a Boston Licensing Board meeting to report chronic issues with intoxicated individuals who visited the establishment after leaving another specific bar in the area (adamg 2021). Further theory on mechanisms of place management could help elucidate whether this strategy is substantially used enough to bias the analytic results from this study. While there is potential that there is enough bias to affect our outcome measure of commercial disturbance rates, the measurement bias that arises from distance between crime offending and crime reporting is present in any study utilizing 911 data, thus the present study is not exceptionally limited in this regard compared to other studies of crime and place.

Finally, we acknowledge that our measure of place management quality, Yelp review scores, is a fairly simplistic strategy for extracting a place management measure from Yelp data. Because we use raw scores without considering their context, the direct meaning of scores is relatively ambiguous. As a result, the focal measure of place management in this study may be biased if the substantive meaning of review scores changes across locations.

For example, the qualities that a fast-food restaurant must have to achieve a 5-star Yelp rating are likely very different from the qualities of the typical 5-star rated fine-dining establishment. This suggests the rating variable may capture variation in restaurant features beyond place management quality. Furthermore, there may be biases across restaurant-types in terms of review frequency and variation, further limiting the utility of using star-ratings to measure place management. To assess the magnitude of measurement bias caused by these factors to understand how these biases impact results from the present study, future research should compare review scores and qualities across restaurant types and evaluate whether review scores are a more effective crime predictor for some business types than others.

For a more precise approach to measuring restaurant features through Yelp reviews, researchers could annotate topics discussed by reviews (e.g., food quality, cleanliness, crime occurrence) to then score restaurants on different parameters rather than using a singular broad measure of place management quality. If enough reviews make references to crime or deviance, this could certainly be a roadmap to developing a more precise measure of crime control among place managers. However, given that the present study draws from over 55,000 reviews, this exercise would require training and testing a natural language processing model, an effort that reaches beyond the scope of the present study. Furthermore, restaurant patrons are only able to observe place management activities within the customer-facing areas of any establishment, so Yelp ratings cannot possibly capture all of the things place managers do behind the scenes to maintain a successful and safe business. That said, restaurant evaluation from the patron perspective likely captures much of the same information that a motivated offender has if they are considering crime in that space, so it is possible this customer review-based measurement strategy is actually the most precise for understanding how place management practices shape offending. We strongly encourage future researchers to develop and evaluate new measurement strategies for place management quality to give the field fuller insight to the processes linking place managers to crime.

Policy Implications

Despite these limitations, the present study suggests that policymakers should be looking toward multi-pronged crime-reduction approaches that holistically consider both place managers and the contexts where they operate. In one potential scenario, a restaurant owner on a quiet, low crime block could start hosting large parties and turn a blind eye to sell as many alcoholic drinks as possible. In the event such activities lead to a pattern of criminal complaints, it would seem logical to apply "problem properties" (see: LISC 2015; Way 2013) intervention strategies where police or other government agencies pressure the business owner to change their conduct. Simultaneously, on the other side of the city there could be an independent restaurant owner who is dedicated to maintaining a safe and pleasant environment for their customers, but because their property is on a block with several vacant properties their employees frequently have to call police because of social disturbances occurring among people who utilize the abandoned buildings for criminal purposes. In that situation, it would not make sense to intervene on the property manager, but to instead utilize an ecological approach that intervenes on the geography by, for example, boarding up the abandoned buildings to make them less accessible to offenders or by allocating policing resources to enhance formal guardianship in the area. Broadly, the best crime reduction policy should be one that is able to respond to specific problems at specific scales rather than using a one-size-fits-all approach.

Conclusion

We propose that scholars of crime and place consider a multi-level theory of place management that accounts for how the effectiveness of place managers are impacted by features of their geographic context. Blocks have features that attract people and offer criminal opportunity, which can explain the number of offenders and targets who are on the block. As these offenders and targets cross path within parcels, it is the job of place managers to control crime. On blocks where there are higher numbers of offenders and targets, the likelihood that a place manager's guardianship abilities become overwhelmed increases. For this reason, one place manager with multiple addresses under their control may vary in place management effectiveness across different geographic locations. With all of this accounted for, we cannot possibly fully explain where crime occurs without including features of both place managers and geographic features in our theoretical models. Echoing past efforts in criminology that argue for multi-level theoretical frameworks (Jones and Pridemore 2019; O'Brien and Ciomek 2022; Wilcox et al. 2018), future research should more concretely investigate how the experience of place managers varies across parcel and geographic contexts to gain a better understanding of features at both analytic scales that can further predict crime.

Appendix A

Factor analysis was conducted on the 9 aforementioned 911 dispatch categories to assess whether any variations of disturbance dispatch could be combined to create categories of commercial disturbances.[11] First, a factor analysis without rotation was conducted on the parcel counts of the 9 dispatch types using the 'psych' R package (Revelle and Revelle 2015). A visual assessment of the eigenvalues produced through this procedure suggested a 2-factor solution. The eigenvalues were additionally analyzed using a knee-point detection algorithm available via the 'SamSPECTRAL' R package (Zare et al. 2015), which also suggested a 2-factor solution.

A 2-factor factor analysis with varimax rotation was conducted to evaluate which dispatch categories compose the two factors (See table below). Results indicate there are two main forms of disturbance issues: social disturbances and noise disturbances. The noise disturbance category includes dispatches for loud music, noise, and parties, while the social disturbance category is then composed of dispatches for verbal disputes, panhandling, drunken behavior, gangs, and non-descript disturbances. Because noise disturbances are relatively rare events (only 38.56% of analyzed parcels had 1 or more noise disturbance dispatches), dispatches from both categories were summed to create a singular measure of commercial disturbance.

[11] Because no external information was needed, this analysis was conducted on a marginally larger sample than the main analyses (31,012 crimes across 1410 parcels).

Factor analysis of disturbance dispatches across parcels (n = 1410)		
	Factor 1	Factor 2
Disturbance—"Default"	0.958	
Disturbance—"Drunks"	0.623	
Disturbance—"Gang"	0.486	
Disturbance—"Panhandling"	0.623	
Disturbance—"Verbal"	0.896	
Investigation—Person Removal	0.810	
Disturbance—Music		0.716
Disturbance—Noise		0.710
Disturbance—Party		0.563

Only loading scores above 0.4 are shown.

Appendix B

Broadly, variance decomposition is conducted by summing variance components and the model intercept and then dividing each value by that sum to describe how the variance is apportioned across the multilevel structure (Raudenbush and Bryk 2002). While this basic strategy is effective for linear models, adjustments need to be made in the case of models analyzing non-linear distributions. Leckie et al. (2020) offer a variance decomposition strategy for negative binomial models that leverages the overdispersion value produced by the model to calculate adjusted marginal variance components. Utilizing their approach, we calculate the percentage of variance apportioned across the four analytic levels. To guide future researchers in conducting such analyses across four-level structures, we have published the R code used for this exercise below.

```
####### Four-Level Variance Decomposition Analysis of Commercial Disturbance Crime.
### Following tutorial from: http://www.bristol.ac.uk/cmm/media/leckie/articles/leckie2020.pdf

##### Read in libraries
library(lme4)
library(haven)
library(ggplot2)
library(glmmTMB)

##### Read in analysis df
bars <—read.csv("../Data/prprtymng_analysis_df.csv", sep = ",", header = TRUE, stringsAsFactors = FALSE)

empty_model <—glmmTMB(crime_per_review ~ 1 +
        (1|OWNER_ID) + (1|Blk_ID_10) + (1|CT_ID_10),
        data = bars,
        na.action = "na.omit",
```

```
        family = nbinom2)
  summary(empty_model)

##### Extract Model Parameters
  ## Extract Model Intercept
  beta0 <—summary(empty_model)$coefficients$cond[1,1]

## Calculate Level-4 variance—extracting from variance table
  sigma_l4 <—summary(empty_model)$varcor$cond$CT_ID_10[1,1]

## Calculate Level-3 variance—extracting from variance table
  sigma_l3 <—summary(empty_model)$varcor$cond$Blk_ID_10[1,1]

## Calculate Level-2 variance—extracting from variance table.
  sigma_l2 <—summary(empty_model)$varcor$cond$OWNER_ID[1,1]

## Calculate overdispersion parameter—calculated as 1/dispersion parameter from model
  alpha <—1/(summary(empty_model)$sigma)

##### Calculate Marginal Expectation and Variance
  ## Marginal Expectation
  expectation <—exp(beta0 + sigma_l2/2 + sigma_l3/2 + sigma_l4/2)

## Marginal variance.
  variance <—expectation + expectation^2*(exp(sigma_l4 + sigma_l3 + sigma_
l2)*(1 + alpha)-1)

##### Calculate Variance Components
  ## Level 4 variance component
  variance4 <—expectation^2*(exp(sigma_l4)-1)

## Level 3 variance component.
  variance3 <—expectation^2*exp(sigma_l4)*(exp(sigma_l3)-1)

## Level 2 variance component.
  variance2 <—expectation^2*exp(sigma_l4)*exp(sigma_l3)*(exp(sigma_l2)-1)

## level 1 variance component
  variance1 <—expectation + expectation^2*exp(sigma_l4 + sigma_l3 + sigma_
l2)*alpha

##### Calculate Variance Proportions
  ##Calculate total variance
  variance_total <—variance1 + variance2 + variance3 + variance4

##Calculate variance proportions
  variance4_prop <—variance4/variance_total.
  variance3_prop <—variance3/variance_total.
  variance2_prop <—variance2/variance_total.
```

variance1_prop <—variance1/variance_total

variance4_prop
variance3_prop
variance2_prop
variance1_prop

Appendix C. Negative Binomial Model with Bootstrapped Standard Errors Evaluating Correlates of Commercial Disturbance Per Yelp Review (*n* = 1070 parcels)

	Model 1 IRR (std. error)	Model 2 IRR (std. error)
Intercept	1.77 (0.76)	0.94 (0.90)
Parcel features		
Mixed use	0.72* (0.09)	0.72 (0.12)
Avg. land value	1.00** (0.00)	1.00*** (0.00)
Avg. square footage	1.00** (0.00)	1.00*** (0.00)
Avg. Yelp rating	0.43*** (0.06)	0.54* (0.14)
Block features		
Ambient population	0.99 (0.01)	0.99 (0.02)
Yelp count	0.91 (0.06)	1.54 (0.56)
Gun crime	1.44* (0.23)	1.20 (0.73)
Violent crime	1.04*** (0.01)	1.04 (0.04)
Private conflict	0.90 (0.06)	0.89 (0.05)
Families in poverty	7.00*** (4.19)	0.31 (1.39)
Percent black	0.66 (0.40)	0.84 (0.09)
Interactions		
Ratings * Yelp count		0.84 (0.09)
Ratings * Guns		1.06 (0.18)
Ratings * Violence		1.00 (0.01)
Ratings * Poverty		2.49 (3.28)

To aid in the interpretation of effect sizes, parameters were standardized (z-scores) prior to analysis.

Appendix D. Hierarchical Negative Binomial Models Evaluating Correlates of Commercial Disturbance Frequency ($n = 1070$ parcels, 1012 owners, 659 blocks)

	Model 1 IRR (std. error)	Model 2 IRR (std. error)
Intercept	0.03 (1.12)***	0.03 (1.10)***
Parcel features		
Mixed use	0.97 (1.12)	0.97 (1.12)
Avg. land value	1.29 (1.05)***	1.36 (1.07)***
Avg. square footage	1.21 (1.04)***	1.36 (1.09)**
Avg. Yelp rating	0.56 (1.05)***	0.54 (1.08)***
Block features		
Ambient population	1.02 (1.05)	1.04 (1.05)
Yelp count	0.75 (1.08)***	0.78 (1.07)***
Gun crime	1.12 (1.10)	1.10 (1.10)
Violent crime	1.55 (1.10)***	1.52 (1.08)***
Private conflict	0.94 (1.10)	0.98 (1.08)
Families in poverty	5.11 (1.72)**	4.57 (1.73)**
Percent black	3.47 (1.61)**	4.11 (1.61)**
Interactions		
Ratings * Yelp count		0.94 (1.06)
Ratings * Guns		1.05 (1.06)
Ratings * Violence		0.97 (1.06)
Ratings * Poverty		1.48 (1.69)
Marginal Block Variance	0.00135	0.00136
Marginal Owner Variance	0.00785	0.00852
Marginal Parcel Variance	0.05824	0.05495

To aid in the interpretation of effect sizes, parameters were grand-mean centered and standardized (z-scores) prior to analysis.

Funding Open access funding provided by Northeastern University Library.

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