Hotspots of Eviction: Guiding Dual-Track Policy Intervention with Spatial Analysis

Wooyong Jung
The Pennsylvania State University
University Park, USA
wjung@psu.edu

Maryam Tabar
University of Texas at San Antonio
San Antonio, USA
maryam.tabar@utsa.edu

Dongwon Lee
The Pennsylvania State University
University Park, USA
dongwon@psu.edu

***Abstract*—Recent studies have shown that a small number of buildings account for a significant portion of evictions in major U.S. cities, suggesting targeted policy interventions for these hotspots. However, focusing solely on eviction volumes can mislead policymakers by implying that property owners are the primary drivers of high eviction rates. This study investigates the spatial structure of eviction filings at the Census Block Group (CBG) level to determine if high eviction rates are due to neighborhood characteristics or other factors like landlords' practices. We addressed three research questions: 1) the relationship between eviction filings due to nonpayment of rent and neighborhood characteristics, 2) the differences between eviction filings due to nonpayment and those for other reasons, and 3) the extent to which high rates of eviction filings in certain CBGs can be attributed to neighborhood characteristics versus unexplained spatial effects. We used Restricted Spatial Generalized Linear Mixed Models (RSGLMMs) with Hamiltonian Monte Carlo (HMC) sampling to estimate neighborhood fixed effects and spatial random effects, using data from Dallas County. Our findings confirm that important neighborhood factors identified in previous studies are consistently significant. Our spatial analysis revealed a noticeable difference between raw eviction filing counts and those adjusted for neighborhood characteristics, identifying CBGs with excessive eviction filings even after accounting for the neighborhood context. Based on these results, we propose a dual-track policy intervention: for hotspot buildings in CBGs with moderate spatial effects, we recommend tenant support measures like rental assistance and legal aid; for those with high spatial effects, we suggest prioritizing in-depth investigations of these buildings and landlord-focused interventions such as education on fair housing laws and landlord-tenant mediation services. All relevant code and data from this project are available in the GitHub repository: https://github.com/yilmajung/eviction_2024_repo_rev.**

***Index Terms*—Eviction, spatial analysis, policy intervention, Bayesian inferences, restricted SGLMMs**

I. Introduction

Evictions have emerged as a complex social issue in the United States, resulting from economic struggles and leading to further social and health problems by thrusting individuals and families into poverty and instability [1]. After the expiration of renter protection programs implemented during the COVID-19 pandemic, many communities have seen a resurgence in eviction filings, with rates often returning to or exceeding pre-pandemic levels [2].

The eviction process in the United States varies by state but generally follows a few common steps. First, the landlord notifies the tenant of a deadline to address any issues that could lead to eviction or to vacate the property. If the tenant does not resolve the issue or leave by the deadline, the landlord can file a lawsuit in court. Both the tenant and the landlord are required to attend the hearing and present their evidence. If the landlord wins the case, the court issues a writ of possession, which allows law enforcement to remove the tenant and their belongings from the property. Because the eviction process involves filing a lawsuit, many studies on eviction have used court records of eviction filings to explore the topic.

With this, recent research has identified patterns where a small number of buildings account for a significant portion of eviction filings [3], [4]. This suggests prioritizing policy interventions targeting landlords and tenants of such buildings. Princeton University's Eviction Lab has made public a dataset detailing the top 100 buildings with the highest eviction filings in major counties, highlighting the disproportionate impact of these buildings on eviction rates[1]. Additionally, recent studies have utilized machine learning (ML) techniques to predict eviction hotspots or the number of filings, demonstrating the predictive capabilities of ML methods [5], [6]. These findings are invaluable for policymakers, enabling them to target resources more effectively. However, focusing solely on eviction filing volumes at these buildings or areas without considering the broader context may create a misleading narrative, suggesting that property owners and their litigious nature are the primary drivers of high eviction rates.

To address this concern, our study investigates the spatial structure of eviction filing sites at the Census Block Group (CBG) level, determining whether the frequency of eviction filings in a particular CBG remains disproportionately high when considering the characteristics of its surrounding neighborhood. By doing so, we aim to discern whether high eviction filing rates in certain CBGs can be attributed to neighborhood characteristics or other unobserved spatial factors, such as landlords' business practices. We compare these findings with known eviction hotspots and propose tailored policy approaches based on specific locations. This approach ensures that policy interventions are not only targeted but also sensitive to the unique dynamics of each neighborhood.

[1]The dataset is available at the Eviction Tacking System website built by the Eviction Lab (https://evictionlab.org/eviction-tracking)

We structured our study around three research questions, RQ1 to RQ3. RQ1 and RQ2 form the foundational phases leading into the deeper analysis of RQ3, our key research question. In RQ1, we explore various neighborhood factors linked to eviction filings due to nonpayment of rent, validating these factors primarily for control purposes. In RQ2, we compare the neighborhood characteristics of eviction filing sites due to nonpayment of rent with those due to other reasons to understand the unique characteristics of nonpayment eviction filings. After controlling for the neighborhood fixed effects validated in RQ1 and 2, in RQ3, we examine the hidden spatial dynamics behind nonpayment eviction filings. In a nutshell, our research questions are:

- **RQ1**: What is the relationship between nonpayment eviction filing sites and the characteristics of their surrounding neighborhoods?
- **RQ2**: What distinguishes nonpayment eviction filings from those caused by other reasons?
- **RQ3**: To what extent can the notably high rates of nonpayment eviction filings in certain CBGs be attributed to unexplained spatial structure, as opposed to neighborhood characteristics?

To answer these questions, we employed Restricted Spatial Generalized Linear Mixed Models (RSGLMMs), which combine Spatial Generalized Mixed Models (SGLMMs) [7], [8] with Restricted Spatial Regression (RSR) methods [9]. RSGLMMs allow us to precisely estimate the fixed effects of neighborhood characteristics while completely distinguishing spatial random effects from the fixed effects. This method captures unobserved spatial heterogeneity, providing critical spatial information for each CBG. We used a Bayesian sampling method, specifically Hamiltonian Monte Carlo (HMC) [10], to estimate parameters.

Our findings for **RQ1** largely align with previous studies [11]–[14]. Economic factors, such as the proportion of households spending over 50% of their income on rent, show a positive association with eviction filings, while median income shows a negative correlation. Demographically, a higher percentage of the black population is positively correlated with eviction filings, while the Asian population ratio is negatively correlated. For **RQ2**, we find that economic factors and housing market dynamics are more closely linked to nonpayment eviction filings. CBGs with more single-unit housing have fewer nonpayment eviction filings but more for other reasons, possibly due to stricter maintenance standards enforced for single-unit residences.

Our spatial random effects analysis (**RQ3**) identified CBGs with higher spatial effects than their neighbors, suggesting the excessive number of eviction filings persists even after accounting for neighborhood characteristics. One explanation of high spatial effects is landlords' stringent practices towards tenants, a critical factor influencing eviction filing volume highlighted in previous studies [3], [15], [16]. Based on our analysis, we propose a dual-track policy intervention targeting eviction hotspot buildings:

- For hotspots in CBGs with moderate spatial effects, direct tenant support measures, such as rental assistance, utility assistance programs, legal aid, and education on tenant rights, would likely be effective.
- For hotspots in CBGs with high spatial effects, in-depth surveys or investigations of these buildings need to be prioritized. Additionally, providing landlord education programs and facilitating landlord-tenant mediation services would be beneficial.

This tailored strategy aims to optimize the use of limited resources to ensure that policy interventions are both impactful and efficient.

II. Related Work

Relocating to a new city involves evaluating various factors like cost of living, transport, safety, healthcare, employment, and local culture. These factors not only shape neighborhood demographics and characteristics within an area but also influence nearby areas, leading to closer areas exhibiting more similar characteristics than those farther apart. While extensive research links neighborhood characteristics to social outcomes like crime [17], [18], quality of life [19], [20], health [21]–[23], and education [24], spatial relationships among neighborhoods often receive less attention, especially in eviction studies. This section reviews eviction literature across economic hardship, demographic characteristics, housing market dynamics, and the built environment, focusing on underexplored spatial dimensions.

A. Economic Hardship

Neighborhoods with similar economic conditions, particularly those classified as low-income neighborhoods, often face higher rates of eviction due to the financial instability of their residents. Numerous studies found a negative correlation between household income and eviction rates or eviction filings [1], [3], [13], [14], [25]–[28]. The situation has been exacerbated by rapidly increasing rents, relatively stagnant incomes among renters, and reduced federal housing assistance, placing a significant burden on the low wage earners [29]. For some, housing costs consume up to 80% of their income [1]. Job loss has also been identified as an obvious precursor to eviction [3], [13], [26], [30], especially with tenants who live paycheck to paycheck, facing not only immediate rent payment issues but potential future payment challenges as well. It increases the likelihood of eviction by landlords [3], [12]. To alleviate these economic challenges, the local governments offer various assistance programs. Recent research highlights the effectiveness of these programs, including housing assistance and vouchers, in protecting families from eviction [31].

B. Demographic Characteristics

Prior research found that the prevalence of eviction differs across various racial and ethnic groups [3], [12], [14]. Data from the Census Bureau Household Pulse Survey indicates that a larger percentage of Black (30%) and Latino (23%) renters fell behind on their rent compared to White (13%) and

Asian (14%) renters during the COVID-19 pandemic [32]. The broader picture clearly shows eviction filings are concentrated in areas predominantly inhabited by specific demographic groups, especially Black and Hispanic people [3], [15], [33]. The racial composition of tenants undeniably influences landlords' decisions on eviction filings. For example, Hispanic tenants face a twofold higher risk of displacement in predominantly White areas compared to non-White neighborhoods in Milwaukee [14], and neighborhoods with primarily Black residents have the highest rates of eviction filings in Cincinnati, whereas areas with fewer Black residents show minimal eviction rates [27]. Furthermore, household size also emerges as a significant factor. Studies indicate that landlords tend to favor smaller families, particularly those without children, due to the potential for children to cause property damage or disturbances [12], [13], [25]. Additionally, urban areas with a higher proportion of residents holding an associate degree or higher experience fewer eviction filings [13], suggesting that educational attainment within a community may play a role in stabilizing tenancies.

C. *Housing Market Dynamics*

The housing market operates fundamentally in the balance between supply and demand. An imbalance, where the demand for housing surpasses the available units, often results in escalating rents, placing a significant financial strain on tenants and increasing the risk of eviction. Particularly in areas where the housing market is tight—characterized by high rents and low vacancy rates—evictions tend to be more prevalent. This can happen when landlords maximize their profits in response to increasing market values, which leads to a spike in eviction rates [3], [15], [28]. Furthermore, shifts in housing value impact the market; renovations or redevelopments often transform low-cost rental units into more expensive housing, diminishing the availability of affordable housing and pushing rents higher [15]. Gentrification in a region further exacerbates eviction rates as landlords move to evict current tenants to upgrade and lease properties at higher rates or sell them for profit [15], [34]. However, the link between gentrification and eviction varies with the stage of gentrification. In the pre-gentrification phase, a positive correlation exists between gentrification and eviction, whereas in neighborhoods that have undergone full gentrification, a negative relationship has been observed [11]. Additionally, the risk of foreclosure, closely related to the mortgage status, can significantly influence eviction filing rates, further complicating the landscape of housing stability [3].

D. *Built Environment*

The built environment or infrastructure of a town is a crucial factor influencing individuals' decisions to move there, with a well-designed environment being more appealing to potential residents and affecting neighboring areas. Studies have indicated that eviction filings are more prevalent in residential areas proximate to the central business district, which offers convenient access to a variety of job opportunities and amenities [30]. The high rental demand in these locations allows landlords to find new tenants with relative ease. Furthermore, it has been observed that evictions are predominantly concentrated in multi-unit structures, where landlords are often large corporate entities [3], [34]. Similarly, in the single-family rental market, eviction filings initiated by large corporate landlords have seen a notable increase [28], [35], highlighting a trend that spans different types of housing and suburban areas [36].

III. Data

To precisely quantify spatial random effects, our study incorporates a comprehensive range of explanatory variables into the fixed effect, most of which are significant predictors of eviction filing counts in prior research. These variables are categorized into economic hardship, demographic characteristics, housing market dynamics, and the built environment. All explanatory variables were standardized to facilitate comparison of the relative strengths of the coefficients. A detailed listing of the variables within each category is provided in Table I, and their sources and collection-and-processing methods are explained in the following subsections.

A. *Eviction Filing Data*

Data on eviction filings were sourced from Dallas County court records, which cover five years from 2017 to 2021. The original dataset included tenants' addresses and the filed amounts, which we grouped by location, or CBG, and eviction filing causes (nonpayment of rent versus other reasons[2]). This categorization allows us to explore distinct patterns within each group, providing a clearer understanding of the dynamics behind nonpayment eviction filing cases. The response variable, the number of eviction filings of each CBG, was converted into the eviction filing rate per 1,000 renter-occupied housing units for each CBG to control for renter density.

B. *Socio-Economic and Demographic Data*

Socio-economic and demographic information at the CBG level was obtained from the American Community Survey (ACS) 5-year data (2017-2021)[3] via the U.S. Census Bureau's Data API. The datasets were integrated using the GEOID for each CBG, which typically includes populations of 600 to 3,000 people [37]. To mitigate measurement bias from tenant protection initiatives like the COVID-19 eviction moratorium[4], we used a pooled cross-sectional analysis for the entire duration and conducted an additional sensitivity analysis using only the pre-pandemic data (2017-2019) to identify any noteworthy changes. Due to the absence of 1-year estimates from the ACS at the CBG level and the Census Bureau's advisory

[2]In cases not related to nonpayment of rent, the sections of the filed amounts are specifically labeled as "Not Nonpayment of Rent."

[3]https://www.census.gov/data/developers/data-sets/acs-5year.html

[4]The CDC's eviction moratorium temporarily suspending residential evictions for rent nonpayment to prevent the spread of COVID-19 was implemented in September 2020 and remained in effect until its expiration on July 31st, 2021 in Texas [38].

against the annual application of 5-year estimates, a trade-off was made to forego temporal trends in favor of spatial detail and measurement accuracy. Out of the 27 variables listed in Table I, three variables—median income, median rent, and the median value of owner-occupied housing units—include missing observations with the missing rates of 2.9%, 19.8%, and 18.9%, respectively.[5] The CBGs, including missing values, mainly consist of very small populations, which may be insufficient for the Census Bureau to produce reliable estimates while maintaining confidentiality. For these CBGs, we filled the missing values with multivariate imputation values based on other observable values.

C. Amenity Data

To collect amenity information, we utilized the OpenStreetMap (OSM) API. Because the OSM API does not provide the CBG-level information, we first divided Dallas County into 93,274 bounding boxes, each measuring 0.1 miles by 0.1 miles. We then counted amenities such as schools, colleges, fire and police stations, restaurants, fast foods, and cafes within each bounding box and summed these counts according to the CBG boundaries. This approach was detailed enough to capture all 1,570 CBGs in the county. Our analysis finally included 1,547 CBGs, excluding those without housing units, such as airports, parks, cemeteries, stadiums, etc.

IV. Research Methods[6]

A. Restricted Spatial Generalized Linear Mixed Models (RSGLMMs)

By exploring the spatial context of evictions, we highlighted the critical need to consider the spatial structure of CBGs. Failing to account for spatial correlations in our analysis models could lead to inaccurate estimations of the relationship between neighborhood characteristics and eviction filing rates. To address this with greater precision while considering spatial correlations, we employ Restricted Spatial Generalized Linear Mixed Models (RSGLMMs). These models enable us to accurately identify fixed effects that focus on the relationships between neighborhood characteristics and eviction filing rates, as well as random effects that manage the spatial correlations among CBGs. Furthermore, we utilize the Restricted Spatial Regression (RSR) method [9] to effectively separate the random effects from the fixed effects, thereby eliminating potential spatial confounding—a common limitation in standard Spatial Generalized Linear Mixed Models (SGLMMs) [9], [40]–[42]. Integrating mixed-effects models with generalized linear models in RSGLMMs allows us to handle spatially dependent and non-Gaussian observations in nature adeptly [8]. The following paragraphs provide a detailed mathematical formulation and the model's implementation.

For observed 1,547 CBGs, let $\boldsymbol{s} = [s_1, \ldots, s_{1,547}]^T$ denote the spatial location of each CBG, then $\boldsymbol{y} = [y(s_1), \ldots, y(s_{1,547})]^T$ represents the eviction filing rates (the number of eviction filings per 1,000 renter-occupying housing units) of each CBG location. We use 27 neighborhood characteristics variables in the fixed effects, and let $\boldsymbol{X} = [x_1(\boldsymbol{s}), x_2(\boldsymbol{s}), \ldots, x_{27}(\boldsymbol{s})]^T$ represent a $1,547 \times 27$ covariate design matrix for those variables. Also, let $\boldsymbol{w} = [w(s_1), \ldots, w(s_{1,547})]^T$ denote a vector containing spatial information of each CBG. Then, with the log link function, the conditional mean of the eviction filing rates, $E[\boldsymbol{y} \mid \boldsymbol{\beta}, \boldsymbol{w}]$, is defined as

$$\log\{E[\boldsymbol{y} \mid \boldsymbol{\beta}, \boldsymbol{w}]\} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{w}, \quad \boldsymbol{w} \sim MVN(\boldsymbol{0}, \boldsymbol{\Sigma}) \tag{1}$$

where $\boldsymbol{\beta}$ is the vector of fixed-effect coefficients, and we assume the spatial effect $\boldsymbol{w}$ coming from a multivariate normal distribution. Then, $\boldsymbol{y} = [y(s_1), \ldots, y(s_{1,547})]^T$ are mutually independent given the spatial random effects, $\boldsymbol{w}(\boldsymbol{s})$ [8], [41].

To appropriately address the discrete spatial structure of the CBGs, we incorporate the intrinsic conditional autoregressive (ICAR) model into the random effects, $\boldsymbol{w}(\boldsymbol{s})$, as a way to contain the spatial structure information. The ICAR model is widely used in spatial statistics to model spatial correlation [42], [43], and it uses a conditional approach, where it assumes that the value of a variable at a particular location is similar to the values at neighboring locations. Since the neighboring CBGs tend to have more similar characteristics (e.g. income level, median rent, racial composition, etc.) than the CBGs further apart, this model's underlying assumption is particularly applicable to our study. The neighboring structure between the 1,547 CBGs is captured by an $1,547 \times 1,547$ first-order adjacency matrix $\boldsymbol{A}$, where $\boldsymbol{A}_{ij} = 1$ if the i-th and j-th CBGs are direct neighbors, and zero otherwise. We calculate the precision matrix, $\boldsymbol{Q}$, by subtracting $\boldsymbol{A}$ from $diag(\boldsymbol{A}\boldsymbol{1})$, where $\boldsymbol{1}$ is an n-dimensional vector of ones. $\boldsymbol{Q}_{ij}$ models the neighborhood structure such that $\boldsymbol{Q}_{ij} < 0$ if i-th and j-th CBGs are neighbors, and $\boldsymbol{Q}_{ij} = 0$, otherwise. Also, $\boldsymbol{Q}_{ii} = -\sum_{i \neq j} \boldsymbol{Q}_{ij}$, which ensures the rows of $\boldsymbol{Q}$ sum to zero. Based on this ICAR model,

$$f(\boldsymbol{w}|\tau) \propto \tau^{\frac{rank(\boldsymbol{Q})}{2}} \exp\big(-\frac{\tau}{2}\boldsymbol{w}^T\boldsymbol{Q}\boldsymbol{w}\big) \tag{2}$$

where τ controls the smoothness of the spatial random effects.

Combining (1) and (2), the likelihood for the model takes the following form

$$L(\boldsymbol{\beta}, \tau; \boldsymbol{y}) = \int_{\mathbb{R}^{1,547}} \left(\prod_{i=1}^{1,547} f_{y_i|w_i}(y_i|w_i, \boldsymbol{\beta}) \right) f_w(\boldsymbol{w}|\tau)\, d\boldsymbol{w}. \tag{3}$$

Due to the high-dimensional structure of the equation, it is infeasible to analytically derive the values of $\boldsymbol{\beta}$ and τ that maximize (3). Instead, sampling methods, such as Bayesian inference, are typically employed to fit the SGLMM. However, before proceeding with a sampling method, we must address an additional challenge: spatial confounding. This issue arises in a conventional SGLMM when there is collinearity between the observed fixed-effect covariates and the spatial random effects, leading to inaccurate parameter interpretations [9], [41], [42]. To overcome spatial confounding, we adopt the

[5]The missing rate for the entire dataset is 1.5%.

[6]All relevant code and data for this project can be accessed at the following GitHub repository: https://github.com/yilmajung/eviction_2024_repo_rev

TABLE I
EXPLANATORY VARIABLES IN RSGLMMS

Category	Fixed Effect	Related Literature
Economic Factors	% of households spending gross rent more than 50% of household income	[1], [3], [5], [6], [13], [25], [26]
	% of households receiving public assistance (including SSI, PAI, SNAP, and Food Stamps)	[31]
	Unemployment rate	[3], [12], [13], [30]
	The median income	[1], [3], [13], [25], [26]
Housing Market Dynamics	% of housing units with a mortgage, contract to purchase, or similar debt	[3], [13], [30]
	% of vacant housing units for rent	-
	Median rent	[3], [15], [28], [39]
	Median value of owner-occupied housing units	[3], [15], [39]
	Rent increase since ACS 2012-2016	[11], [12], [15], [39]
	House value increase since ACS 2012-2016	[11], [12], [15], [34], [39]
Demographic Characteristics	Median age	[13]
	% of black population	[14], [15], [32]
	% of Hispanic population	[14], [32]
	% of Asian population	[32]
	% of population with educational attainment at the graduate or professional level	[3], [5], [6], [13]
	% of own children (under 18 years) living with a married couple	[3], [12], [13], [25], [32]
	% of own children (under 18 years) living with a female householder (no spouse)	[3], [12], [13], [25]
	% of own children (under 18 years) living with a male householder (no spouse)	[12], [25]
	% of nonfamily households	-
Built Environment	% of workers with travel time to work less than 30 minutes	[30]
	% of workers with travel time to work 60 or more minutes	[30]
	% of single-unit detached and attached housing units	[3], [15]
	% of households with no internet access	-
	# of fire and police stations per capita	-
	# of cafes and restaurants (including fast foods) per capita	-
	# of colleges or universities per capita	-
	# of schools per capita	-

Restricted Spatial Regression (RSR) method [9], [40], [44], converting our model to Restricted SGLMMs. The RSR method involves constraining the spatial random effects, $\boldsymbol{w}$, to be orthogonal to the fixed effects. This transforms (1) into

$$\begin{aligned}\boldsymbol{X}\boldsymbol{\beta}+\boldsymbol{w} &= \boldsymbol{X}\boldsymbol{\beta}+P_{[\boldsymbol{X}]}\boldsymbol{w}+P_{[\boldsymbol{X}]}^{\perp}\boldsymbol{w}\\ &= \boldsymbol{X}\boldsymbol{\beta}+\boldsymbol{X}(\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{w}+P_{[\boldsymbol{X}]}^{\perp}\boldsymbol{w}\\ &= \boldsymbol{X}[\boldsymbol{\beta}+(\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{w}]+P_{[\boldsymbol{X}]}^{\perp}\boldsymbol{w}\\ &= \boldsymbol{X}\tilde{\boldsymbol{\beta}}+P_{[\boldsymbol{X}]}^{\perp}\boldsymbol{w}\end{aligned}$$

where $P_{[\boldsymbol{X}]}$ denotes orthogonal projection onto the span of $\boldsymbol{X}$, and $P_{[\boldsymbol{X}]}^{\perp}$ is its complement. After fitting the fixed and transformed random effects, the valid values of $\hat{\boldsymbol{\beta}}$ can be calculated using the a posteriori adjustment [9], [41] through

$$\hat{\boldsymbol{\beta}}^{(k)}=\tilde{\boldsymbol{\beta}}^{(k)}-(\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{w}^{(k)} \tag{4}$$

where $\tilde{\boldsymbol{\beta}}$ is the covariate coefficient before the adjustment, and k denotes the k-th sample.

B. Hamiltonian Monte Carlo (HMC)

In addition to the challenge of spatial confounding, another significant issue with SGLMMs is the computational burden posed by high-dimensional random effects. While some studies suggest a projection-based reduced-dimensional strategy—employing a select number of principal components of random effects to significantly enhance computational efficiency [41], [42]—this method falls short of providing a comprehensive understanding of the spatial random effects within each Census Block Group (CBG). Given our research objective (RQ3) to ascertain the spatial effect on every CBG, we opt for the Hamiltonian Monte Carlo (HMC) technique to optimize computational efficiency. Unlike conventional random walk-based algorithms such as the Metropolis-Hastings (MH) algorithm, HMC excels in navigating high-dimensional parameter spaces by leveraging gradient information and auxiliary momentum variables [10].

Moreover, while the MH algorithm may struggle with correlated parameters—often requiring numerous iterations to traverse the distribution and thoroughly explore the parameter space—the use of gradient information in HMC steers the sampling process toward the most pertinent areas of the parameter space [10]. Given the potential correlations among our model's parameters and its intricate, high-dimensional spatial configuration, HMC emerges as the most suitable and effective method for our purposes. Consequently, we implement the RSGLMMs via the HMC approach to analyze the eviction filings and neighborhood data, utilizing the *Stan* programming language for model fitting. Once the transformed covariates, $\tilde{\boldsymbol{\beta}}$, and spatial random effects, $P_{[\boldsymbol{X}]}^{\perp}\boldsymbol{w}$, are estimated, we convert the transformed covariates back to their valid $\hat{\boldsymbol{\beta}}$ using (4).

V. RESULTS

A. Model Diagnostics

To verify that the Markov chains reached their equilibrium distribution, we tracked the $\hat{R}$ statistic for each parameter. This statistic compares the average variance within each chain to the variance between chains. Ideally, if all chains converge to the equilibrium, the $\hat{R}$ ratio will equal one; otherwise, it will exceed one [45]. According to heuristic guidelines, samples with an $\hat{R}$ value below 1.01 are considered reliably converged [45], [46], while values below 1.05 are generally deemed acceptable [46]. Additionally, we monitored bulk and tail effective sample size (ESS) for each parameter. In order to get reliable estimates of posterior credible intervals, at least 100 ESS per Markov chain is recommended [46], emphasizing the importance of both convergence metrics and sufficient sampling depth for robust statistical inference.

1) Model Assessment: Our analysis involved four Markov chains and 113,000 samplings per each, including 5,000 initial warm-up iterations and a thinning factor of three to retain only every third observation, mitigating autocorrelation effects. Consequently, we acquired 144,000 samples per parameter ($= \frac{113{,}000-5{,}000}{3} \times 4$ chains), observed a mean $\hat{R}$ value of 1.010 with the maximum of 1.015, and obtained enough ESS for every parameter: 1,864 ESS on average with the minimum of 174.37 ESS. These diagnostic indicators confirm that the four chains mixed effectively and achieved convergence, therefore the coefficient estimates are reliable.

2) Sensitivity Analysis for the Pandemic Influence: To examine the impact of the pandemic on our study findings, we conducted a parallel experiment using data exclusively from the pre-pandemic period (2017-2019). Our analysis showed that the directional effects of 26 out of the 27 coefficients remained consistent. For 23 of the coefficients, even their credible intervals overlapped, indicating minimal disparities between the datasets. Although three coefficients—rent increases, the ratio of the Black population, and single-unit housing—displayed significant differences, they maintained a consistent direction. The ratio of own children living with a female householder was the only variable that exhibited a significant difference in the opposite direction compared to the comprehensive dataset. It may suggest the pandemic has disproportionately affected these households. However, since a deeper analysis of this factor falls outside our research scope, we do not explore it further. Instead, we conclude that these findings largely confirm the reliability of our results, regardless of the pandemic's influence.

B. RQ1: Neighborhood Characteristics of Nonpayment Eviction Filing Hotspots

The results of our analysis on nonpayment eviction filing cases are summarized in Figure 1, indicated by red bars. Economically, a high rent burden (more than 50% of household income) and lower household income correlate with increased eviction filing rates. CBGs with a higher proportion of households receiving social assistance show reduced eviction filing rates, indicating that public support for low-income families helps mitigate evictions. However, the impact of social assistance is relatively modest—a 4.7% decrease in eviction filing rates for each standard deviation (SD) increase in households receiving assistance, compared to a 13.1% reduction for each SD increase in median household income.

In terms of housing market dynamics, higher eviction rates are associated with a greater ratio of vacant rental units, likely reflecting higher tenant turnover in areas with increased eviction rates. Additionally, CBGs with a higher number of mortgaged housing units experience increased eviction filings, indicating that areas with more mortgaged properties may face greater housing insecurity, potentially due to the risk of foreclosure. This can be further influenced by recent shifts in the housing market, where large corporate landlords acquire foreclosed properties at discounted rates and subsequently rent them out [3]. This trend aligns with previous research pointing out that post-foreclosure single-family homes are significantly more likely to experience eviction filings [3].

Regarding gentrification, changes in median house value and rent between ACS 2012-2016 and 2017-2021 data show a subtle and insignificant negative association with eviction filings. This could be due to different stages of gentrification, where the initial displacement of low-income tenants is followed by an influx of more financially stable residents [11]. This is further evidenced by the negative correlation between the eviction filing rates and median rent and house value, suggesting that CBGs with higher rents and house values are less sensitive to evictions.

Demographically, the proportion of Black residents significantly correlates with eviction filings, with a 17.6% increase in eviction filing rates for each SD increase in the Black population ratio. Families with children, regardless of marital status, face discrimination in the rental market [12], [13]. Female householders with children are more likely to encounter eviction filings than their male counterparts. Unlike previous research, we did not find a significant correlation between educational attainment and eviction filing rates. However, CBGs with a higher ratio of Asian residents tend to have lower eviction filing rates.

In the built environment, CBGs with predominantly single-unit structures report fewer eviction filings, suggesting that private landlords are less likely to initiate evictions compared to large corporate landlords. Higher accessibility to amenities such as restaurants, cafes, and fire and police stations correlates with higher eviction filing rates. Conversely, CBGs that include colleges or universities report fewer eviction filings, likely because a significant proportion of residents are on-campus students, making eviction filing rare.

These RQ1 results largely align with the key findings from previous studies, providing reliability of our models' fixed effect component and a safe starting point for analyzing the subsequent spatial random effect in RQ3.

C. RQ2: Nonpayment vs. Other Reasons

To explore the distinguishable neighborhood characteristics associated with nonpayment eviction filings more clearly, we compared them with those characteristics related to evictions due to other reasons, such as lease violations, property damage, illegal activities, etc. A distinct observation is that evic-

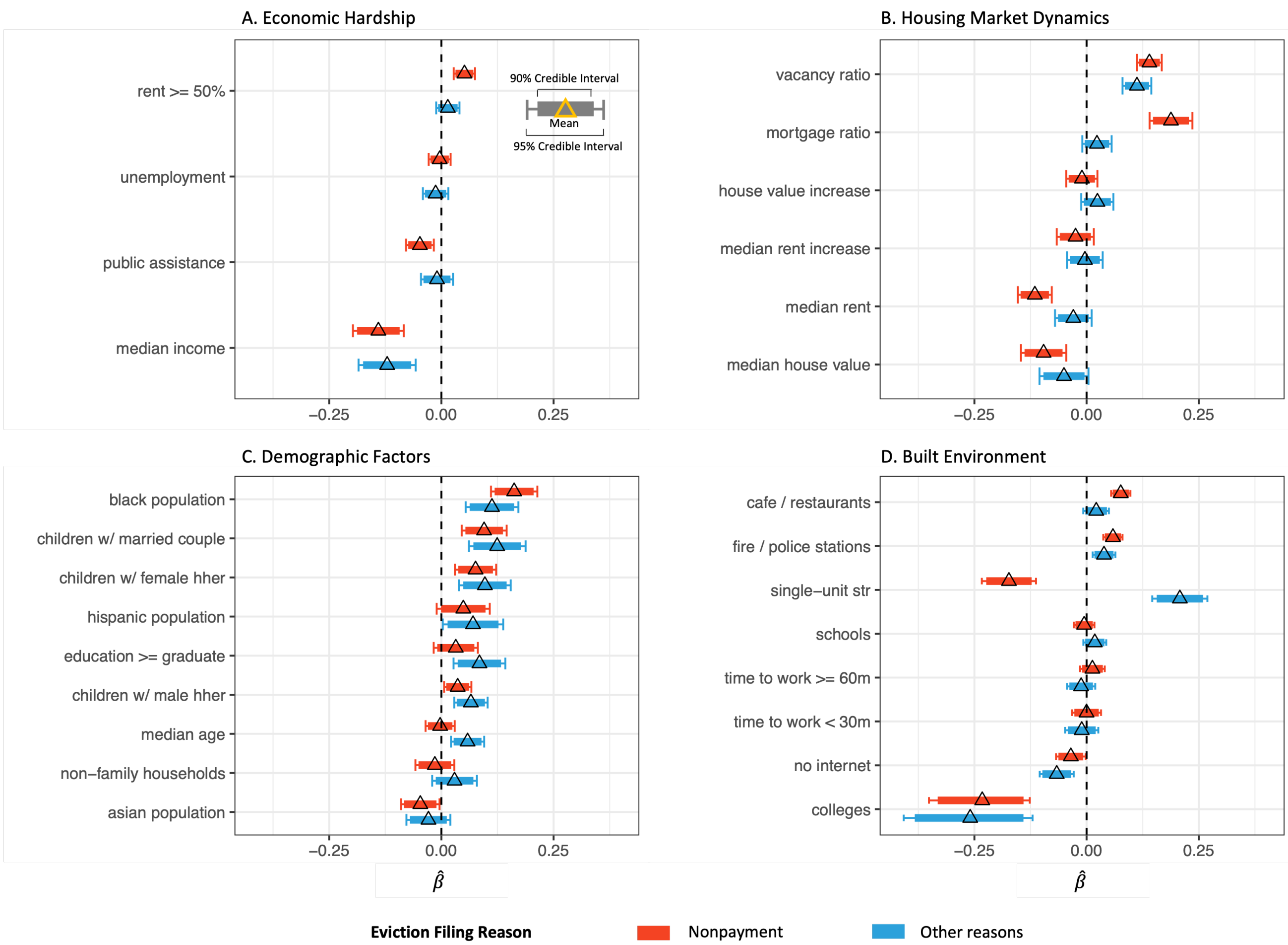

Fig. 1. Posterior Distributions of the Fixed Effects. The estimated covariate coefficients are denoted as $\hat{\beta}$ on the horizontal axes. The blue bars represent nonpayment eviction filings, while the red bars correspond to filings for any other reasons. The thickness of the bars conveys the credible interval's confidence level: thicker bars signify a 90% credible interval, and narrower bars indicate a 95% credible interval.

tions for reasons other than nonpayment exhibit less sensitivity to economic and housing market factors. Except for household median income and the ratio of vacant housing units, other variables within these categories do not significantly influence evictions due to other reasons. Instead, these types of evictions are more closely linked to demographic factors, including the ratios of Black and Hispanic populations and the presence of families with children.

The most notable distinction between the two types of evictions is observed in the proportion of single-unit homes: areas with a higher percentage of single-unit residences tend to have fewer nonpayment eviction filings but more filings for other reasons. This could be due to the stricter maintenance and property standards often required of single-unit homes, such as yard upkeep, proper trash disposal, and general maintenance, which are not typically enforced in multi-unit buildings. Therefore, tenants in single-unit houses might have higher incomes and more stable employment, making them less likely to fall behind on rent but possibly more susceptible to evictions for lease violations unrelated to payment.

D. RQ3: Spatial Random Effects

After adjusting for neighborhood characteristics, we investigate the spatial random effects for each CBG. These effects reveal spatial patterns that are not explained by neighborhood characteristics alone. Figure 2 contrasts the raw eviction filing rate by CBG (Figure 2-A) with the spatial effects after neighborhood effects have been accounted for (Figure 2-B). We ranked each CBG based on their eviction filing rates and the magnitude of spatial effects, categorizing them into five quintiles. The figure highlights marked differences, particularly in areas denoted by blue triangles and red inverted triangles. Because these areas show significant disparities in demographic composition, income, and rent levels, usually far higher eviction filings occur in the blue area than in the other as seen in Figure 2-A. By controlling for neighborhood effects, however, we uncover the underlying spatial dynamics of eviction filings (Figure 2-B).

One possible and convincing interpretation of these spatial effects is their reflection of landlords' behavior, addressed as a crucial factor influencing eviction filings in prior research [3],

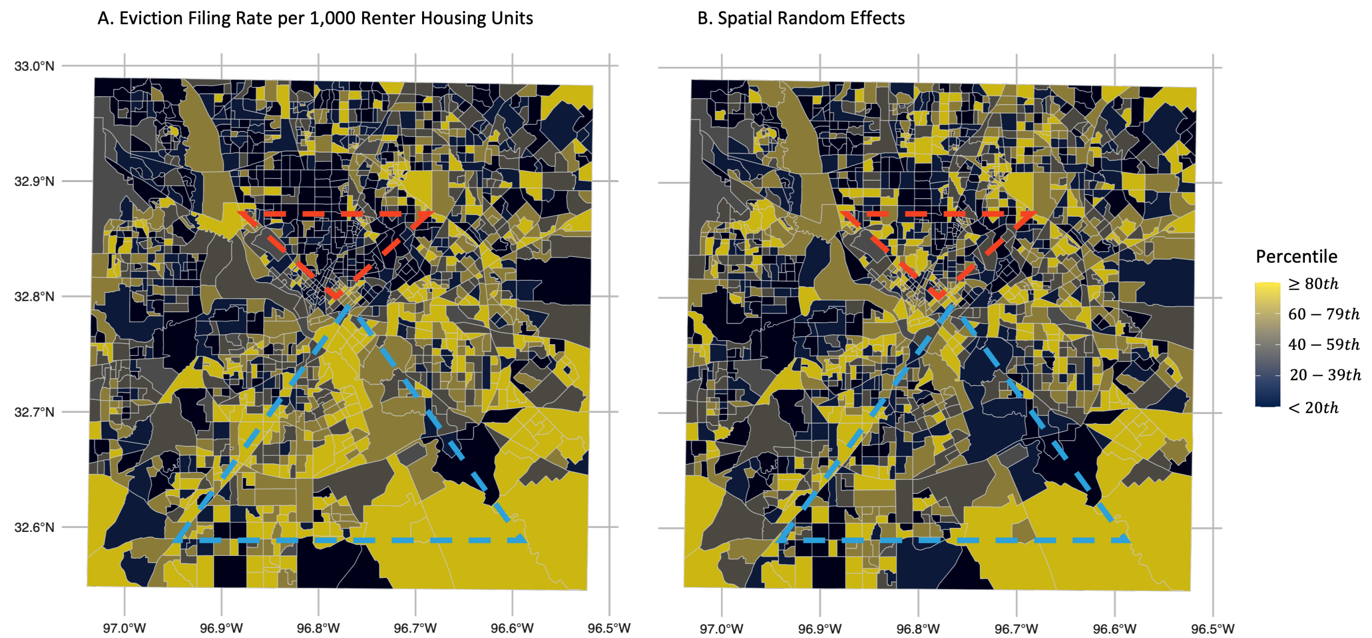

Fig. 2. Eviction Filing Rates and Spatial Random Effects. The left figure (A) displays a map of the raw eviction filing rate by CBG, while the right figure (B) shows the spatial effects, adjusted for neighborhood characteristics. The red and blue triangles highlight areas where the spatial effects significantly unveil the underlying spatial patterns hidden by the raw eviction filing rate.

[15], [16], yet not included in our fixed effects due to data limitations. Specifically, landlords in the light yellow CBGs, marked by unusually high eviction rates, possibly adopt more stringent enforcement practices against tenants. This insight forms the basis for the policy recommendations discussed in the Discussion section, suggesting targeted interventions to address the identified disparities in spatial effects across CBGs.

VI. Takeaways and Policy Implications

Recent studies on evictions have highlighted that a small number of landlords account for a significant proportion of eviction filings, suggesting that targeting these landlords and tenants for policy interventions could effectively reduce evictions [3], [4]. However, our study underscores the importance of examining the spatial structure of eviction filing locations beyond judging eviction filing hotspots merely based on the number of filings.

We contextualized the eviction filing rates of each CBG within their surrounding neighborhoods, investigating whether disproportionate filing rates are associated with neighborhood characteristics or other spatial factors, such as landlords' stringent actions. Our findings reveal a marked difference between raw eviction filing counts and those adjusted for neighborhood-related factors. While most CBGs' eviction rates can be explained by local economic and demographic characteristics, housing market conditions, and the built environment (indicating moderate spatial random effects), some CBGs record excessive eviction filings even after accounting for these factors (indicating significantly higher spatial effects).

This suggests that focusing solely on the volume of eviction filings in specific buildings, without considering the broader neighborhood context, could unfairly imply that property owners' litigious behavior is the main factor driving high eviction rates. Recognizing the strategic value of prioritizing eviction filing hotspots due to budget and time constraints, we propose a dual-track approach to interventions for eviction hotspots based on their location:

1) **Hotspot buildings in moderate spatial-effect areas**: The elevated eviction filings in these hotspot buildings (blue dots in Figure 3) can be understood in the context of their neighborhood characteristics. This suggests that the increase in eviction filings is largely due to neighborhood conditions rather than solely to landlords' litigious behavior. Consequently, policies aimed at enhancing the overall neighborhood environment will be more impactful. Our analysis in response to **RQ1** indicates that factors such as low household income, a high rent-to-income burden, and the presence of larger families with children are significantly linked to elevated eviction rates. Addressing these issues through measures like rental assistance vouchers, utility assistance programs, affordable housing projects, and providing legal aid and education on tenant rights would be beneficial.
2) **Hotspot buildings in high spatial-effect areas**: In these areas (red dots in Figure 3), the excessive volume of eviction filings cannot be explained by neighborhood characteristics alone. Even after accounting for all neighborhood-related factors, eviction rates remain abnormally high. In these cases, policy practitioners should prioritize conducting comprehensive surveys or investigations of these hotspot buildings. Since land-

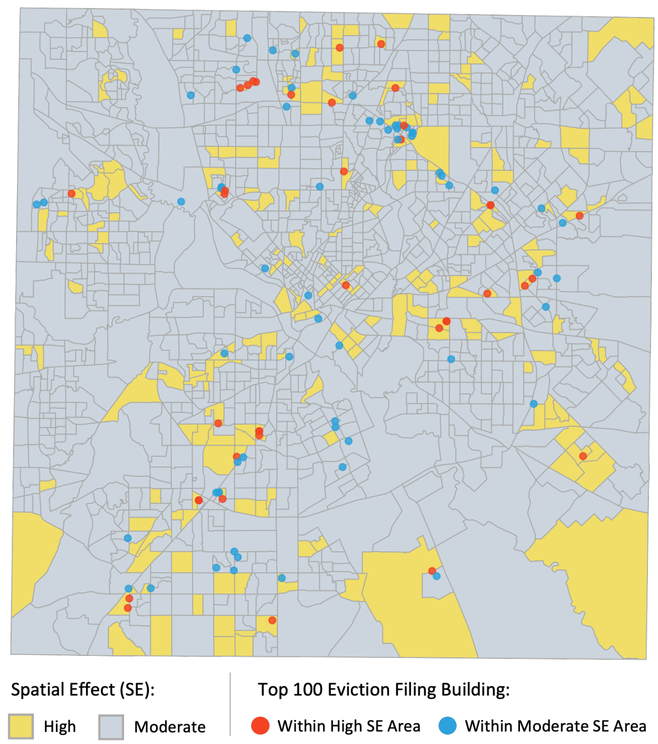

Fig. 3. Top-100 Eviction Filing Buildings. The buildings indicated by red dots represent the top 100 buildings located in CBGs with high spatial effects, while the blue dots indicate the top 100 buildings in CBGs with moderate spatial effects. While the threshold between high and moderate spatial effect CBGs in this figure is set arbitrarily at the 95th percentile, determining the threshold should depend on the town's available resources and budget.

lords' behavior or business practices are suspected to be key factors, implementing policy measures that directly target landlords may be beneficial. Potential measures could include education and training sessions for landlords on fair housing laws and tenant rights, introducing landlord-tenant mediation services, and offering tax incentives to landlords who maintain affordable rental prices.

To provide a clearer explanation of the dual-track policy intervention above, we set an arbitrary threshold to distinguish high spatial effect CBGs from moderate ones, using the 95th percentile as a cutoff point in Figure 3. However, determining this threshold should ideally take into account the town's available resources and budget. In practical terms, we recommend prioritizing CBGs with the highest spatial effects first.

VII. Discussion

A. Generalizing Findings

This study provides a framework for policymakers to design more effective and targeted interventions by differentiating between eviction filing hotspots driven by neighborhood characteristics and those influenced by unexplained spatial effects. Although our findings may not directly apply to other towns with different natural and built environments due to the limitations of a case study, the methodologies used to identify spatial structures can be applied to them for comparison and the development of best practices across different urban contexts. Most of all, housing authorities and urban planners can use this method to allocate resources more efficiently. To expand current research further, the framework proposed in this study can be applied to longitudinal policy studies to observe the lasting effects of specific interventions on eviction rates. This will offer a more in-depth and precise understanding of causality and impact after contextualizing neighborhood factors and spatial correlation.

B. Limitations

Several limitations are worth considering for future studies. We posited that spatial random effects largely reflect landlords' behavior, which is a crucial factor not included in the fixed-effect component of our analysis. Despite our thorough attempt to incorporate all significant factors identified in previous research, some pivotal factors may have been overlooked. We recommend that policymakers conduct detailed surveys of hotspot buildings in areas with high spatial effects before implementing landlord-targeted policy interventions. If these surveys uncover previously unrecognized factors—limitations of our current model—future research should address them. Additionally, the phenomenon of serial eviction filings against the same tenants presented a complex issue [15], [16]. While such serial filings might inflate the eviction counts in certain CBGs, we interpreted these instances as indicative of landlords' stringent business practices, treating them as manifestations of landlords' behavior within the spatial random effects. Future studies should consider distinct spatial analyses on serial versus nonserial eviction filings as valuable additions to the eviction literature.

VIII. Conclusion

This study explores the complex issue of eviction filings, with a particular focus on revealing the spatial structure of filing locations while taking into account the characteristics of surrounding neighborhoods. Our findings for RQ1 and RQ2 mostly align with previous studies, highlighting critical neighborhood factors significantly linked to eviction filing rates. Crucially, our analysis of spatial random effects for RQ3 offers valuable insights into the underlying spatial dynamics of eviction filings. This information assists policymakers and practitioners in pinpointing eviction hotspots that require thorough investigation versus those where comprehensive neighborhood improvements could be beneficial. By adopting this tailored approach, we can better allocate limited resources, enhancing the effectiveness and efficiency of policy interventions.

Acknowledgment

This work was partially supported by NSF awards #1940076 and #1934782, along with the 2023 seed funding from the Center for Socially Responsible Artificial Intelligence (CSRAI) at Penn State.

References

[1] M. Desmond, "Eviction and the reproduction of urban poverty," *American journal of sociology*, vol. 118, no. 1, pp. 88–133, 2012.

[2] C. Vallejo, J. Haas, and P. Hepburn, "Preliminary analysis: Eviction filing patterns in 2022," Mar 2023. [Online]. Available: https://evictionlab.org/ets-report-2022/

[3] E. L. Raymond, R. Duckworth, B. Miller, M. Lucas, and S. Pokharel, "From foreclosure to eviction: Housing insecurity in corporate-owned single-family rentals," *Cityscape*, vol. 20, no. 3, pp. 159–188, 2018.

[4] D. Q. Rutan and M. Desmond, "The concentrated geography of eviction," *The ANNALS of the American Academy of Political and Social Science*, vol. 693, no. 1, pp. 64–81, 2021.

[5] M. Tabar, W. Jung, A. Yadav, O. W. Chavez, A. Flores, and D. Lee, "Forecasting the number of tenants at-risk of formal eviction: A machine learning approach to inform public policy," in *Proceedings of the Thirty-First International Joint Conference on Artificial Intelligence*, 2022, pp. 5178–5184.

[6] M. Tabar, W. Jung, A. Yadav, O. Wilson Chavez, A. Flores, and D. Lee, "Warner: Weakly-supervised neural network to identify eviction filing hotspots in the absence of court records," in *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*, 2022, pp. 3514–3523.

[7] O. F. Christensen, G. O. Roberts, and M. Sköld, "Robust markov chain monte carlo methods for spatial generalized linear mixed models," *Journal of Computational and Graphical Statistics*, vol. 15, no. 1, pp. 1–17, 2006.

[8] P. J. Diggle, J. A. Tawn, and R. A. Moyeed, "Model-based geostatistics," *Journal of the Royal Statistical Society Series C: Applied Statistics*, vol. 47, no. 3, pp. 299–350, 1998.

[9] E. M. Hanks, E. M. Schliep, M. B. Hooten, and J. A. Hoeting, "Restricted spatial regression in practice: geostatistical models, confounding, and robustness under model misspecification," *Environmetrics*, vol. 26, no. 4, pp. 243–254, 2015.

[10] M. Betancourt, "A conceptual introduction to hamiltonian monte carlo," *arXiv preprint arXiv:1701.02434*, 2017.

[11] A. Chum, "The impact of gentrification on residential evictions," *Urban Geography*, vol. 36, no. 7, pp. 1083–1098, 2015.

[12] M. Desmond and C. Gershenson, "Who gets evicted? assessing individual, neighborhood, and network factors," *Social science research*, vol. 62, pp. 362–377, 2017.

[13] R. Goodspeed, E. Benton, and K. Slugg, "Eviction case filings and neighborhood characteristics in urban and rural places: A michigan statewide analysis," *Housing Policy Debate*, vol. 31, no. 3-5, pp. 717–735, 2021.

[14] D. Greenberg, C. Gershenson, and M. Desmond, "Discrimination in evictions: empirical evidence and legal challenges," *Harv. CR-CLL Rev.*, vol. 51, p. 115, 2016.

[15] D. Immergluck, J. Ernsthausen, S. Earl, and A. Powell, "Evictions, large owners, and serial filings: Findings from atlanta," *Housing Studies*, vol. 35, no. 5, pp. 903–924, 2020.

[16] L. Leung, P. Hepburn, and M. Desmond, "Serial evictions: Property managers, tenants, and civil court sanctions," *Social Forces, first published on September*, vol. 11, 2020.

[17] I. Y. Sun, R. Triplett, and R. R. Gainey, "Neighborhood characteristics and crime: A test of sampson and groves' model of social disorganization," *W. Criminology Rev.*, vol. 5, p. 1, 2004.

[18] S. P. Varano, J. A. Schafer, J. M. Cancino, and M. L. Swatt, "Constructing crime: Neighborhood characteristics and police recording behavior," *Journal of criminal justice*, vol. 37, no. 6, pp. 553–563, 2009.

[19] K. Mouratidis, "Neighborhood characteristics, neighborhood satisfaction, and well-being: The links with neighborhood deprivation," *Land use policy*, vol. 99, p. 104886, 2020.

[20] M. J. Sirgy and T. Cornwell, "How neighborhood features affect quality of life," *Social indicators research*, vol. 59, pp. 79–114, 2002.

[21] M. S. Bryan, J. Sun, J. Jagai, D. E. Horton, A. Montgomery, R. Sargis, and M. Argos, "Coronavirus disease 2019 (covid-19) mortality and neighborhood characteristics in chicago," *Annals of epidemiology*, vol. 56, pp. 47–54, 2021.

[22] P. Eibich, C. Krekel, I. Demuth, and G. G. Wagner, "Associations between neighborhood characteristics, well-being and health vary over the life course," *Gerontology*, vol. 62, no. 3, pp. 362–370, 2016.

[23] M. M. Weden, R. M. Carpiano, and S. A. Robert, "Subjective and objective neighborhood characteristics and adult health," *Social science & medicine*, vol. 66, no. 6, pp. 1256–1270, 2008.

[24] J. W. Ainsworth, "Why does it take a village? the mediation of neighborhood effects on educational achievement," *Social forces*, vol. 81, no. 1, pp. 117–152, 2002.

[25] M. Desmond, W. An, R. Winkler, and T. Ferriss, "Evicting children," *Social Forces*, vol. 92, no. 1, pp. 303–327, 2013.

[26] M. Desmond, *Evicted: Poverty and profit in the American city*. Crown, 2016.

[27] E. Johns-Wolfe, "" you are being asked to leave the premises": A study of eviction in cincinnati and hamilton county, ohio, 2014-2017," *The Cincinnati Project*, 2018.

[28] E. Seymour and J. Akers, "Building the eviction economy: Speculation, precarity, and eviction in detroit," *Urban Affairs Review*, vol. 57, no. 1, pp. 35–69, 2021.

[29] A. Mazzara, "Census: Income-rent gap grew in 2018," Sep 2019. [Online]. Available: https://www.cbpp.org/blog/census-income-rent-gap-grew-in-2018

[30] K. Kim, I. Garcia, and S. Brewer, "Spatial relationship between eviction filings, neighborhood characteristics, and proximity to the central business district: A case study of salt lake county, utah," *Housing Policy Debate*, vol. 31, no. 3-5, pp. 601–626, 2021.

[31] I. Lundberg, S. L. Gold, L. Donnelly, J. Brooks-Gunn, and S. S. McLanahan, "Government assistance protects low-income families from eviction," *Journal of Policy Analysis and Management*, vol. 40, no. 1, pp. 107–127, 2021.

[32] S. Parrott, A. Sherman, J. Llobrera, A. Mazzara, J. Beltrán, and M. Leachman, "More relief needed to alleviate hardship," *Center on Budget and Policy Priorities, July*, vol. 21, 2020.

[33] D. S. Massey, "American apartheid: Segregation and the making of the underclass," *American journal of sociology*, vol. 96, no. 2, pp. 329–357, 1990.

[34] E. L. Raymond, B. Miller, M. McKinney, and J. Braun, "Gentrifying atlanta: Investor purchases of rental housing, evictions, and the displacement of black residents," *Housing Policy Debate*, vol. 31, no. 3-5, pp. 818–834, 2021.

[35] E. L. Raymond, R. Duckworth, B. Miller, M. Lucas, and S. Pokharel, "Corporate landlords, institutional investors, and displacement: Eviction rates in singlefamily rentals," *FRB Atlanta community and economic development discussion paper*, no. 2016-4, 2016.

[36] D. Q. Rutan, P. Hepburn, and M. Desmond, "The suburbanization of eviction: Increasing displacement and inequality within american suburbs," *RSF: The Russell Sage Foundation Journal of the Social Sciences*, vol. 9, no. 1, pp. 104–125, 2023.

[37] US Census Bureau, "Glossary," Apr 2022. [Online]. Available: https://www.census.gov/programs-surveys/geography/about/glossary.html

[38] Texas State Law Library, "The cdc eviction moratorium ends on saturday, july 31st," Jul 2021. [Online]. Available: https://www.sll.texas.gov/spotlight/2021/07/the-cdc-eviction-moratorium-ends-july-31st/

[39] D. Immergluck, A. Carpenter, and A. Lueders, "Hot city, cool city: explaining neighbourhood-level losses in low-cost rental housing in southern us cities," *International Journal of Housing Policy*, vol. 18, no. 3, pp. 454–478, 2018.

[40] J. Hughes and M. Haran, "Dimension reduction and alleviation of confounding for spatial generalized linear mixed models," *Journal of the Royal Statistical Society Series B: Statistical Methodology*, vol. 75, no. 1, pp. 139–159, 2013.

[41] Y. Guan and M. Haran, "A computationally efficient projection-based approach for spatial generalized linear mixed models," *Journal of Computational and Graphical Statistics*, vol. 27, no. 4, pp. 701–714, 2018.

[42] ——, "Fast expectation-maximization algorithms for spatial generalized linear mixed models," *arXiv preprint arXiv:1909.05440*, 2019.

[43] J. Besag, "Bayesian image restoration with two applications in spatial statistics (with discussion)," *Ann I Stat Math 43*, vol. 1, p. 59, 1991.

[44] J. S. Hodges and B. J. Reich, "Adding spatially-correlated errors can mess up the fixed effect you love," *The American Statistician*, vol. 64, no. 4, pp. 325–334, 2010.

[45] A. Gelman, A. Vehtari, D. Simpson, C. C. Margossian, B. Carpenter, Y. Yao, L. Kennedy, J. Gabry, P.-C. Bürkner, and M. Modrák, "Bayesian workflow," *arXiv preprint arXiv:2011.01808*, 2020.

[46] Stan Development Team, "Stan user's guide version 2.35." [Online]. Available: https://mc-stan.org/docs/stan-users-guide/index.html