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A National Analysis of the Spatial Patterns and Correlates of Evictions in the United States

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Abstract

This national study investigates the spatial patterns and correlates of housing evictions in the U.S., a critical crisis of local and national significance. A national data set on county-level eviction rates was obtained from Princeton University's Eviction Lab database, and the data on risk factors of eviction were acquired from the Centers for Disease Control and Prevention (CDC)'s Social Vulnerability Index (SVI). First, we examined disparate patterns of evictions across U.S. counties, followed by a hot spot analysis to determine clusters of counties with significantly high or low values of eviction rates. The analysis concluded with multiple regression to investigate the associations of eviction rates and 15 CDC SVI indicators. Evictions are most prevalent in populous urban or metropolitan counties; however, eviction rates can be higher in less-populous suburban counties even nonmetropolitan communities. Clusters of counties with significantly high eviction rates (i.e., hot spots) were mainly concentrated in lower Michigan-upper Indiana and the along the east coast that spanned Virginia, North Carolina, and South Carolina. The spatial regression model explained a moderate degree of the variations of eviction rates and social vulnerability indicators including income, minority population, single-parent, unemployment rate, apartment living, and low education status were most helpful predictors of eviction. This national study can inform government resource allocation efforts where it provides new insights into the spatial disparities and potential contributing factors of eviction rates across U.S. counties, thus enhancing our understanding of the eviction crisis nationwide.

Keywords Eviction · Spatial disparities · Hot spots · Social vulnerability · Urban-rural

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Introduction

Eviction refers to a phenomenon that tenants are displaced from their residential rental dwelling units by landlords for a variety of causes including failure to pay monthly rent or violations of nuisance laws (e.g., health, safety, and illegal activity). Nationwide, it has been estimated that millions of evictions occur each year in the United States (U.S.), constituting a critical and under-researched crisis faced by renters who are most likely to be poor and racial/ethnic minorities (Hartman & Robinson, 2003). Despite the increasing prevalence of evictions in the U.S. in recent years, less research has been conducted to examine its geographic aspects and correlates largely due to the lack of data. While it is most reported in inner-city neighborhoods and large cities, eviction cases happen in nearly any type of community, ranging from metropolitan areas to rural communities (IMCA, 2020; Goodspeed et al., 2021; Hepburn et al., 2022). For example, some of the latest research suggests that poverty and its associated risk for eviction have increased at an alarming rate in the suburban United States especially since the early 2000's (Carol & Yi, 2021). Additionally, the recent COVID-19 pandemic has exacerbated eviction risk nationally and this context is relevant in terms of the coming economic recovery from the pandemic.

Existing studies of eviction in the U.S. have examined patterns of evictions performed at the municipal or neighborhood level (Robinson & Steil, 2021; Seymour & Ackers, 2021a, b; Teresa, 2018), yet little is understood about the characteristics of eviction across counties nationwide. The total count of evictions within a given area can be difficult to capture empirically because some evictions occur outside of the formal institutions that systematically count evictions (Gromis & Desmond, 2021). Studies of eviction are nevertheless essential, however, as there exists lack of consensus as to the scope and magnitude of various risk factors of eviction. The objective of this national study is to investigate the spatial patterns and correlates of formal, court-ordered housing evictions across U.S. counties, with a particular focus on social vulnerability indicators determined by the U.S. Centers for Disease Control and Prevention (CDC). First, we examined disparate patterns of evictions across U.S. counties through the lens of USDA urban-rural continuum codes. Then a hot spot analysis was conducted to determine clusters of counties that had significantly high or low values of eviction rates compared to the national average. Last multiple regression including a spatial lag model were performed to investigate the associations of eviction rates and 15 CDC Social Vulnerability Index (SVI) indicators.

Literature Review

Studies of eviction in the U.S. have considered possible associations between eviction and a variety of risk factors for eviction. These studies have tended to focus on analyses of individual cities or states. Some studies have found significant associations between eviction and variables such as urban financial institutions (Sims, 2016; Harrison et al., 2021; Seymour & Ackers, 2021a) and gentrification (Chum, 2015; Kim et al., 2021), while others have found strong associations with household and other demographic factors like race and poverty as risk factors for eviction (Desmond & Gershenson, 2017; Ramiller, 2021; Robinson & Steil, 2021; Immergluck et al., 2020; Seymour & Ackers, 2021b; Finger, 2019; Teresa, 2018). Studies vary in the weight given to different variables as predictors of eviction, and there exists a lack of universal consensus in the literature as to why some households in the United States experience eviction. A more nuanced understanding of the risk factors of eviction is therefore warranted.

Factors of urban financial institutions and gentrification have been considered in several analyses of eviction in the United States. Revel Sims (2016) studied displacement in Los Angeles and found four factors that contributed to evictions including financial institutions and investment funds, the organization of local and transnational resources through local development-oriented growth machines, property-based organizations and self-assessment mechanisms, and real estate finance intermediaries such as predatory lending agents. Another study by Harrison et al. (2021) found that senior, subsidized multifamily properties in metropolitan Atlanta, Georgia had significantly lower rates of eviction than market rate properties in that area. Further, a study of eviction in Las Vegas, Nevada by Eric Seymour and Joshua Akers (2021a) found that the existence of institutional investors in single family rentals as well as large residential motel operators were associated with higher rates of evictions. Eviction has also been discussed explicitly in relation to gentrification. Outside of the U.S., but remaining within the western context, a study by Chum (2015) includes the first analysis of displacement through eviction in gentrifying neighborhoods. The study concluded both that evictions in Toronto, CA, were significantly heightened in neighborhoods that are undergoing the early stages of gentrification, and that neighborhoods that were gentrified over 10 years ago have significantly reduced eviction rates. Another study by Kim et al. (2021) found a significant relationship between eviction filings and the built environment characteristics in Salt Lake City, Utah, including proximity to the central business district (CBD) and light rail transit stations, intersection density, and land use mix score. Overall, the authors found that the concentration of housing evictions was negatively associated with an increase in the distance to CBD when CBD was transformed into gentrified areas led by new high-end apartment constructions during the housing boom since 2000.

Other research has extended studies of eviction to the neighborhood level as well as social demographic variables such as race and poverty status. Some research findings emphasize or suggest the role of these variables in causing evictions. A study by Ramiller (2021) suggests that evictions may be most likely to occur at the early stages of development-driven neighborhood change in Seattle, Washington. Further, Robinson and Steil (2021) examined the characteristics of properties and property owners at the neighborhood level in Boston to capture differences between types of housing and forms of eviction. The authors found that eviction filings were more likely to occur in recently constructed or renovated rental properties with higher values compared to other properties in the same neighborhood. They also found that evictions were more likely to occur in neighborhoods with higher shares of Black renters. Another study by Immergluck et al. (2020) found that at the property level, neighborhood race, and in particular properties in Black neighborhoods, is a strong predictor of nonserial eviction filings, which are a form of eviction filing that are more likely to result in tenant displacement. Similarly, Eric Seymour and Joshua Akers' (2021b) study of evictions and housing foreclosures in Detroit's single family residential neighborhoods shed light on the relationship between housing insecurity and evictions through illustrating investors' methods for profiting from the constrained housing options of low-income and credit-impaired households. In Davida Finger's (2019) study of eviction in New Orleans, the percentage of population that is African American was found to be the strongest predictor of evictions. Likewise, in a study of eviction in Richmond, VA, Teresa (2018) found that neighborhood racial composition was a significant factor associated with eviction rates, even after controlling for income, property value, and other characteristics. Teresa found that as the shares of the African American population increases, the eviction rate increases, and the inverse was found for increases in non-Hispanic white populations. Another recent study by Desmond and Gershenson (2017) of Milwaukee renters found that while gentrification did not act as a predictor variable of eviction, other variables including family size, job loss, neighborhood crime, and network disadvantage were identified as significant and robust predictors of eviction. Similarly, a study by Merritt and Farnworth (2021) found that the implementation of tenant-friendly policies in neighborhoods across the United States helped to reduce eviction disparities but not eliminate them especially in communities of color and majority-Black neighborhoods.

Debate remains as to the weight that differing factors hold in causing eviction. To begin to address this gap, the concept of social vulnerability is offered within this study as a venue through which spatial patterns of eviction can be related to at the national scale. As a concept, social vulnerability describes combinations of social, cultural, economic, political, and institutional processes that shape the differential experience of hazards (Adger, 2006; Turner et al., 2003; Birkmann, 2013). While some understand social vulnerability as intrinsically attached to place, social vulnerability is also viewed by some to be rooted in and emerge from the interaction of forces that range from macro-economic and institutional to micro-economic and situational (Spielman et al., 2020, p. 419). The concept of social vulnerability is built around the idea that who you are and where you live can have a profound impact on how you prepare for, experience, and recover from environmental hazards or man-made hardships (Ngo, 2003; Laska & Morrow, 2006). The social scientific literature explains that differential experiences of, and responses to, hazards are rooted in social vulnerability, while additionally explaining that the same hazard event can be experienced differently by different people along different spatial gradients. The concept of social vulnerability has been used predominantly in studies of natural hazards (see Uitto, 1998; Frigerio et al., 2016; Schmidtlein et al., 2011), although others have used this idea to study phenomena outside of natural hazards. Galster et al. (2016), for instance, created a social vulnerability index to study the relationship between adolescent neighborhood context and economic outcomes for low-income African Americans and Latinos. Similarly, Walks (2013) studied the relationship between several sociodemographic and housing variables and levels of household debt across Canadian cities to understand the spatiality of vulnerability resulting from debt.

Considering social vulnerability in relation to eviction may open questions of social vulnerability to macroeconomic, microeconomic, and situational forces as eviction is attributable to various socioeconomic risk factors. Likewise, considering the spatial patterns of eviction and social vulnerability together may add to the debate as to whether eviction is the consequence of particular demographic characteristics or perhaps of the result of other structural processes, such as that of rapid neighborhood economic change. For instance, Lens et al. found that court-based evictions are more likely to occur in areas with low-income households and racial and ethnic minorities than in areas experiencing rapid change including rising rents and changing demographics (2020, p. 912). Others conversely explain that evictions occur in rapidly changing neighborhoods, and more specifically, they occur as the result of broader structural economic forces (Slater, 2006, p. 738; Smith, 2008, p.196; Shaw, 2008, p. 192). This contrast in the literature speaks to the question as to whether eviction is caused by factors of social vulnerability or structural economic factors, and furthermore the need for a more nuanced understanding as to the causes of eviction in the U.S.

Data and Methods

Data on home evictions were obtained from Princeton University's Eviction Lab that has constructed the first national database of evictions spanning from 2000 to 2016 in the U.S. The data was collected at both the census tract and county levels and is comprised of tract-level formal eviction court records and county-level, state-reported court statistics on landlord-tenant cases (Desmond et al., 2018). Court records gathered from 13 states include information detailing the opening and resolution of individual eviction cases, while state-reported, county-level court statistics gathered from 27 states include case-volume data from reports, landlord/tenant case data, and other sources. For this study, county-level eviction data for the year 2016 was used, and as data from the Eviction Lab only includes formal eviction records and statistics, data capturing eviction outside of legal reliance on court institutions was not considered for this analysis. This choice constitutes a limitation of our study as recent findings from a national study by Gromis and Desmond (2021) found that displacement estimates that focus only on formal evictions miss a substantial proportion of forced displacement that occur outside the purview of the courts. However, currently the only available quantitative data on informal evictions at the national level are collected through the 2017 American Housing Survey, which captures eviction cases from a sample within the 51 largest metropolitan areas by population, rather than at the county level (HUD, 2021). Instead of using raw counts, we used eviction rate which is the percent of renter-occupied residential dwellings that have been evicted by court orders. In this study, we limit our analyses to 2,494 counties in the contiguous 48 states as 614 counties had data unavailable.

In addition, we used the CDC and Agency for Toxic Substances and Disease Registry's (CDC/ATSDR) Social Vulnerability Index (SVI) for the year 2014 to investigate the socioeconomic correlates of eviction rates. The SVI data set measures the relative vulnerability of U.S. communities (i.e., census tracts or counties) to natural or human-made disasters based on 15 indicators with data originally collected by the American Community Survey of the U.S. Census Bureau (CDC, 2020). The index includes variables that can be used by public health officials and emergency response planners to identify communities that may need support in the context of disasters or hazardous events. In other words, it can be used to contextualize and quantify factors such as poverty, lack of access to transportation, and crowded housing that may weaken a community's ability to prevent human suffering or financial loss in a disaster. The SVI data covers four themes including Socioeconomic Status (i.e., variables "% Below Poverty", "% Unemployed", "Income", and "% No High School Diploma"), Household Composition and Disability (i.e., variables % Aged 65 and older, % Aged 17 and Younger, % Civilians with a Disability, and % Single Parent Households), Minority Status and Language (i.e., variables "% Minority" and "% Speaks English 'Less than Well'"), and Housing Type and Transportation (i.e., variables "% Multi-Unit Structures", "% Mobile Homes", "% Crowding", "% No Vehicle", and "% Group Quarters"). Each of the 15 SVI indicators were used as explanatory variables in our subsequent analyses to explain the variations of eviction rates across U.S. counties. We hypothesized that these SVI indicators were positively correlated with county-level eviction rates. Furthermore, we included a binary dummy variable in the regression analysis to predict the differences between metropolitan (coded as 1) and nonmetropolitan counties (coded as 0) in eviction rates. As suggested by the literature (Mazur, 2016), it is hypothesized that metropolitan counties were more likely to have more severe eviction problems than rural communities.

In order to examine the spatial disparities in eviction rate across communities nationwide, we summarized county-level eviction data to urban-rural continuum locale codes designated by the U.S. Department of Agriculture (USDA), which use counties as the basic building blocks. The USDA urban-rural locale codes distinguish between metropolitan and nonmetropolitan areas based on the size of a county's urban population and its location relative to metropolitan areas of different sizes. Counties located inside metropolitan statistical areas (MSAs) are divided into 3 subcategories ranging in population size from over one million persons to fewer than 250,000 persons. Counties located outside any metropolitan area are assigned to one of six subcategories depending on the size of its urban population and whether it is adjacent to a metropolitan area. These six subcategories include completely rural nonmetro or metro areas (population < 2,500) which are either adjacent or nonadjacent to a metro area, nonmetro areas (urban population of 2,500 – 19,999) which are either adjacent or nonadjacent to a metro area, and nonmetro areas (urban population > 20,000) which are either adjacent or nonadjacent to a metro area. Moreover, we examined the differences between urban and suburban communities within metropolitan areas using the U.S. Census Bureau's classification of central (or urban) counties and outlying (or suburban) counties.

Next, we performed a global Moran's I diagnosis to reveal if the distribution of eviction rates across U.S. counties had a clustered pattern. The global Moran's I test is considered a de facto standard for determining spatial autocorrelation. Moran's I models calculate the difference between a target feature and the mean of all features, as well as the difference between each neighbor and the mean. The value allows us to define the overall importance of spatial characteristics in affecting a given object in space as well as the extent of the relationship between objects (Mitchell, 1999). Following the global Moran's I diagnosis, we used a local spatial statistical approach or hot spot analysis (i.e., Getis-Ord Gi*) to identify clusters of nearby counties that had significantly high values of eviction rates or low values in comparison to the national average. For both global and local spatial statistical analyses, a contiguity-based queen spatial weight was used to determine the neighboring features (i.e., counties) for each county. A geographic lens construes hot spots as neighborhoods of values that are significantly higher/greater/different from surrounding areas (Getis & Ord, 1996; Ord & Getis, 2001) based off predetermined cut off levels and territorial values (Wilson et al., 2005). This lens is considered by some to offer the greatest potential understanding the geographic patterns of housing landscape via the examination of spatially oriented data (Lepczyk et al., 2007).

Lastly, multiple linear regression models were conducted using the 15 CDC SVI indicators as independent variables to predict the spatial variations of eviction rates, which was used as the dependent variable. We performed ordinary least squares (OLS) regression first and spatial regression models afterwards considering the existence of spatial autocorrelation (or dependence) among nearby counties violates the basic assumptions of linear regression model. A growing number of urban and social science studies have addressed the issue of spatial autocorrelation and recommended the use of spatial regression models (i.e., spatial lag or spatial error models) (Anselin, 2005, 2009; Basu & Thibodeau, 1998; Voss et al., 2006). Spatial error models account for spatial dependence in the error term, while spatial lag models account for spatial correlation in the dependent variable which in turn emphasizes the importance of neighborhood effects. We decided to run spatial lag model as an alternative to ordinary least squares (OLS) regression because it is not only theoretically more reasonable but also justified by the decision rule of spatial regression model selection that involves diagnosis of the statistics of Lagrange Multiplier (lag), Lagrange Multiplier (error), Robust LM (lag), and Robust LM (error) (Anselin, 2005).

Results

Differentials in Eviction Rates Across USDA Urban-Rural Locales

Summary statistics for USDA urban-rural locale codes indicate that counties in medium-sized MSAs had the highest average eviction rate (i.e., 3.013%, Table 1) followed by small MSAs and nonmetro counties adjacent to a MSA with urban population equal or larger than 20,000. Contrary to conventional wisdom, counties in large MSA of 1 million or more population had an average eviction rate of 2.295%, which is much lower than the averages for medium and small MSA counties. Within metropolitan areas, central counties showed slightly higher average eviction rates

Table 1 Average eviction rates in U.S. counties of different urban-rural locale categories

USDA urban-rural locale codes	Number of counties	Eviction rate (%)
Counties in large MSAs of 1 million or more population	360	2.295
- Central Counties	*212*	*2.296*
- Outlying Counties	*148*	*2.272*
Counties in medium-sized MSAs of 250,000–1 million population	291	3.013
- Central Counties	*181*	*3.021*
- Outlying Counties	*110*	*2.893*
Counties in small MSAs of fewer than 250,000 population	276	2.469
- Central Counties	*181*	*2.500*
- Outlying Counties	*95*	*1.903*
Nonmetro counties – Urban population ≥ 20,000, adjacent to a MSA	178	2.318
Nonmetro counties – Urban population ≥ 20,000, not adjacent to a MSA	66	1.919
Nonmetro counties – Urban population 2,500 – 19,999, adjacent to a MSA	451	2.141
Nonmetro counties – Urban population 2,500 – 19,999, not adjacent to a MSA	346	1.044
Nonmetro counties – Completely rural or < 2,500 urban population, adjacent to a MSA	194	1.317
Nonmetro counties – Completely rural or < 2,500 urban population, not adjacent to a MSA	332	0.651

than outlying or suburban counties as we expected, given that eviction rates tend to be higher in cities compared to suburbs (Hepburn et al., 2022). Further, we found that this pattern is consistent for large, medium and small metropolitan areas. In comparison to metropolitan areas, nonmetropolitan counties generally had a much lower magnitude of eviction levels, which is largely because rural communities tend to have higher homeownership rates or lower rates of renter-occupied than their metropolitan counterparts and eviction only happened to renters (Goodspeed et al., 2021; Mazur, 2016; Scally et al., 2018).

A close examination of the top 25 counties that had the highest eviction rates provided more detailed information about the complexity of eviction rates across geographic locales (Table 2). Overall, 14 of the top 25 counties are located in the state of South Carolina, 7 are located in Virginia, 2 are located in Michigan, and 1 is located each in Mississippi and Georgia respectively. As expected, 10 large MSA and 7 medium sized MSA counties were on this list. However, 4 small MSA and 4 additional nonmetropolitan counties also made this listing. Petersburg City,

Table 2 Top 25 counties or county equivalents that had the highest evication rates

#	County	State	Evictions	Eviction rate	Locale
1	Petersburg City	Virginian	1402	17.56	Large MSA
2	Cherokee	South Carolina	1178	16.41	Nonmetro
3	Florence	South Carolina	2978	16.13	Small MSA
4	Hopewell City	Virginia	685	15.69	Large MSA
5	Portsmouth City	Virginia	2469	15.07	Large MSA
6	Berkeley	South Carolina	3116	14.21	Medium-Sized MSA
7	Laurens	South Carolina	1032	13.37	Medium-Sized MSA
8	Darlington	South Carolina	1003	12.42	Small MSA
9	Richmond City	Virginia	6345	11.44	Large MSA
10	Richland	South Carolina	7183	11.37	Medium-Sized MSA
11	Chester	South Carolina	397	10.97	Large MSA
12	Union	South Carolina	385	10.94	Medium-Sized MSA
13	Hampton City	Virginia	2538	10.49	Large MSA
14	Georgetown	South Carolina	634	10.4	Nonmetro
15	Marlboro	South Carolina	448	10.37	Nonmetro
16	Newport News City	Virginia	3732	10.23	Large MSA
17	Colleton	South Carolina	412	10.21	Nonmetro
18	Muskegon	Michigan	1772	10.1	Small MSA
19	Anderson	South Carolina	2304	10.09	Medium-Sized MSA
20	Prince George	Virginia	299	9.6	Large MSA
21	Calhoun	Michigan	1628	9.56	Small MSA
22	Aiken	South Carolina	1827	9.33	Medium-Sized MSA
23	Tunica	Mississippi	218	9.31	Large MSA
24	Charleston	South Carolina	6226	9.3	Medium-Sized MSA
25	Paulding	Georgia	1000	9.2	Large MSA

Virginia, a large MSA county equivalent located in the outskirts of the Richmond-Petersburg metropolitan area, ranked the highest, while Cherokee County and Florence in South Carolina, which were designated as small MSA and nonmetropolitan counties separately, ranked the second and third respectively.

Uneven Geographic Distribution of Evictions

Eviction rates across U.S. counties had an extremely uneven geographic distribution ranging from as low as 0 to as high as 17.6% (Fig. 1). Regardless of areas that had missing data, counties in the Midwestern (especially in Michigan, Ohio, Indiana, etc.) and Southeastern regions (i.e., Virginia, South Carolina, and North Carolina) had the highest eviction rates while those in the nation's Western and Northeastern regions generally had low eviction rates as illustrated in Fig. 1. This finding enriches the landscape of prior studies which have shown both coasts of the United States to have had the highest concentrations of home value hot spots (Gale & Roy, 2022), as well as the most substantial persistence of housing hyper-vacancies especially in neighborhoods with large black populations and high poverty rates (Harrison & Immergluck, 2020). Another relevant study of housing growth hotspots in the North Central states of the U.S. found that the total area of all hot spots in this region increased significantly between 1940 and 2000, exhibiting areas of absolute growth

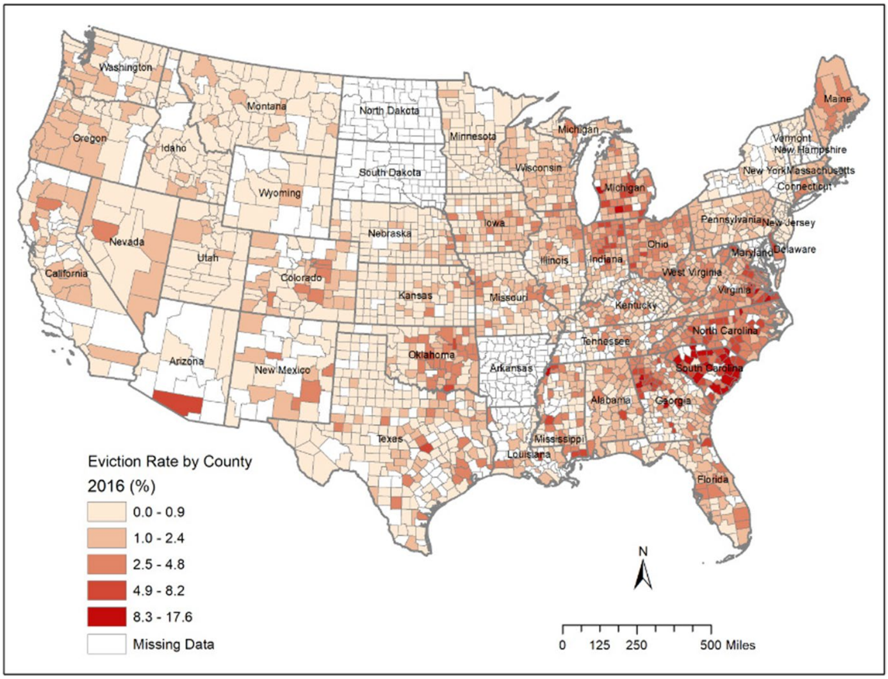

Fig. 1 Map of the geographic distribution of eviction rates across U.S. counties (2016). *ESRI's ArcMap Program was used to create this figure

around urban centers and areas of percent growth throughout rural locations, despite most of this landscape never actually containing any housing growth hotspots (Lepczyk et al., 2007). Further, a comparison of the geographic distribution of housing eviction rates across U.S. counties and the distribution of SVI indicators (i.e., poverty rate and minorities) suggest strong positive spatial associations between them (Fig. 2). Counties displaying high eviction rates also tend to show elevated levels of poverty and % of the population that is minorities, especially in the southeastern region of the country.

A global Moran's I diagnosis (i.e., Moran's $I = 0.512$ with Z-score of 40.993 and $p\text{-value} < 0.001$) indicates that eviction rates across the conterminous U.S. demonstrated a clustered pattern in which neighboring counties, especially those in metropolitan areas, with high rates were concentrated next to each other and vice versa for nonmetropolitan counties with low eviction rates. Figure 3 illustrates the results of a subsequent hot spot analysis of eviction rates using counties as the unit of analysis, with areas shown in dark red depicting hot spots that had significantly high rates of evictions. It is important to note that if a county is diagnosed as a hot spot, it means that this county and its surrounding neighbors (i.e., any county that shared borders with it) had significantly larger eviction rates than the national average, not just this county alone. It is most remarkable to see the two large clusters of spatially congruent counties diagnosed as hot spots congregated in two regions including lower Michigan-upper Indiana and along the east coast that spanned Virginia, North

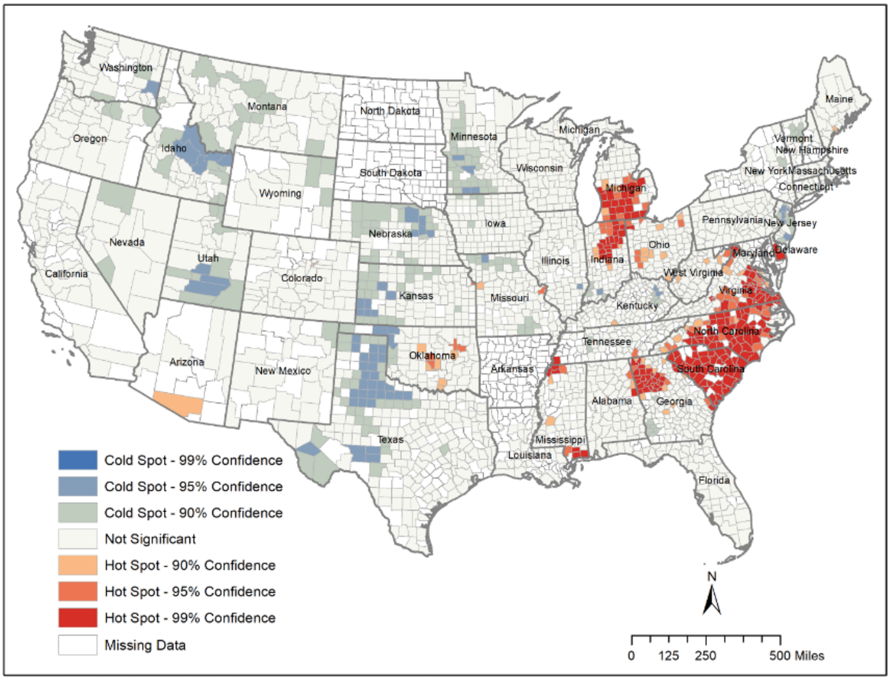

Fig. 2 Map of hot and cold spots of counties measured by eviction rate using Getis-Ord Gi* statistic. *ESRI's ArcMap Program was used to create this figure

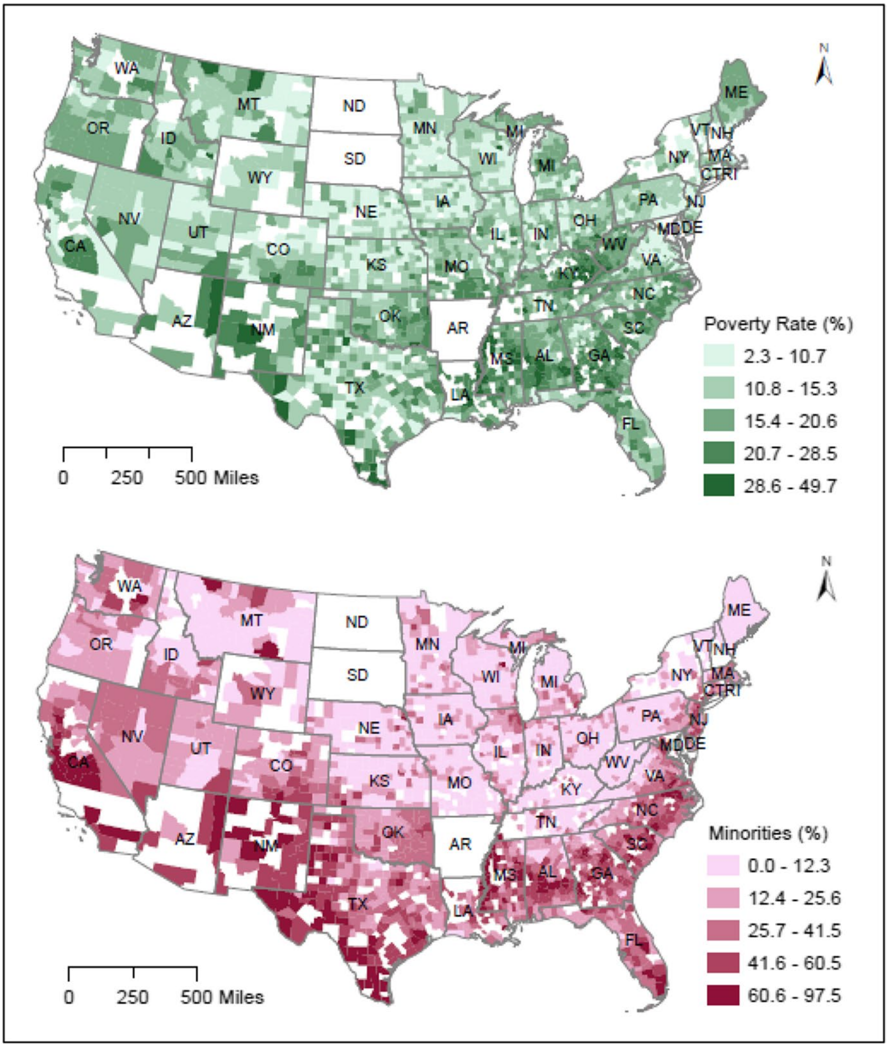

Fig. 3 Maps of poverty rates and percent of population that is minorities across U.S. counties (2014)

Carolina, and South Carolina, which echoed our observations from Fig. 1. Additionally, several small clusters of hot spots can be identified in other parts of the country including the northwestern portion of the state of Georgia, the southwestern corner of Tennessee and northwestern Mississippi, the coastal area of Mississippi, and central Oklahoma. On the contrary, counties depicted in dark blue were diagnosed as cold spots, indicating their significantly lower eviction rates than the national average. Large pockets of cold spots are mainly scattered in the western region of the country with a preponderance of nonmetropolitan counties. An examination of the statistics suggests that counties labelled as hot spots had much higher eviction rates compared with their cold spots counterparts (Table 3). For example, the mean

Table 3 Descriptive statistics of hot and cold spots of counties by eviction rate (%)

Hot spot / cold spot	Average eviction rate (%)	Count of counties	MSAs					Non-MSA
			Large	Medium-sized	Small	Central	Outlying	Non-MSA
Cold spot – 99% confidence	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Cold spot – 95% confidence	0.081	67	3	7	2	11	8	55
Cold spot – 90% confidence	0.190	186	5	2	10	41	11	169
Not significant	1.253	1918	259	201	233	743	343	1225
Hot spot – 99% confidence	5.568	207	67	47	19	126	46	74
Hot spot – 95% confidence	3.454	61	14	20	5	37	14	22
Hot spot – 90% confidence	2.962	55	12	14	7	29	11	22
Hot spot total		323	93	81	31	192	71	118

eviction rate for the 207 counties that were designated as hot spots at the 99% confidence level was 5.568%, which was over 70 times of the average rate for the 67 counties that were diagnosed as cold spots (i.e., 0.081%). Whereas hot spots can be observed in any USDA locale code, nearly 64% hot spots were spotted in metropolitan areas including 93 large, 81 medium sized and 31 small MSAs. Likewise, within metropolitan areas, more counties identified as hot spots by eviction rate were central counties than suburban ones (i.e., 192 vs. 71).

Regression Results

All 15 independent variables showed statistically significant correlations except unemployment rate, disability, and households with no vehicle in the OLS regression model (Table 4). Positive associations were found between eviction rate and population with no high school diploma, minority population, single parent households, housing structures with more than ten units, and metropolitan locality, which are all hallmarks of socioeconomic vulnerability that tend to prompt eviction. Multicollinearity among variables was not present as our analyses resulted in no VIF levels above 7.

Negative correlations were observed between eviction rate and poverty, per capita income, aged 65 and older, aged 17 and under, speaks English "less than well", living in mobile homes, overcrowding, and persons living in group quarters. It is understandable to see a negative relationship of eviction and per capita income because eviction has become commonplace among low-income households in the United States (Desmond, 2022). As for poverty and group quarters variables, standard definitions may justify these negative correlations. For instance, one explanation for the conflicting sign of poverty could be due to the threshold used by the U.S. Census Bureau to define poverty. If a household's income exists just below the income threshold, the Census defines them as being in poverty; however, maybe those households continue to afford rent especially given records of historically high levels of rent-burden since the Great Recession (Colburn & Allen, 2018). Further, the U.S. Census (2021) defines group quarters as a place where people live or stay, in a group living arrangement, that is owned or managed by an entity or organization providing housing and/or services for the residents. These definitions may help explain the negative correlations found in our study between these variables and eviction.

However, the negative results found for remaining variables were surprising given the existence of a variety of suggestions and findings from other studies. For limited English proficiency, some scholarship stresses the potential of this variable to exacerbate eviction in the United States (Kuehnhoff, 2010; Goldstein et al., 2019; Remus & Garland, 2021). One study of housing discrimination in evictions at the local municipal level, however, found discrimination among Hispanic households, even after controlling for language (Greenberg, Gershenson, & Desmond, 2016). Studies of eviction and children also have varied results. One study found prevalence of housing evictions among children born within U.S. cities (Lundberg & Donnelly (2019). Additionally, several studies have found a connection between children and

Table 4 Regression results of eviction rates against social vulnerability indicators across U.S. counties ($n = 2{,}494$)

Variables	Ordinary least squares model		Spatial lag model	
	Coefficient	Standard error	Coefficient	Standard error
Spatially weighted eviction rate	n/a	n/a	0.629***	0.017
Constant	7.675***	0.833	3.816***	0.646
Poverty rate (%)	-0.078***	0.011	-0.041***	0.008
Unemployment rate (%)	0.027	0.017	-0.007	0.014
Per capita income ($ thousand)	-0.093***	0.011	-0.075***	0.008
No high school diploma (%)	0.026*	0.011	-0.006	0.008–0.038
Age 65+ (%)	-0.075***	0.013	-0.038***	0.010
Age 17- (%)	-0.129***	0.018	-0.048***	0.014
Disabled (%)	0.007	0.013	0.025*	0.010
Single parent households (%)	0.154***	0.018	0.108***	0.014
Minority population (%)	0.030***	0.003	0.016***	0.002
Speak English “less than well” (%)	-0.155***	0.021	-0.057***	0.016
Structures w/ 10 + housing units (%)	0.052***	0.011	0.052***	0.008
Living in mobile homes (%)	-0.016**	0.005	-0.018***	0.004
Overcrowding (%)	-0.168***	0.027	-0.094***	0.021
Households with no vehicle	-0.007	0.014	0.000	0.011
Persons living in group quarters (%)	-0.096***	0.010	-0.057***	0.008
Metro locale	0.819***	0.084	0.405***	0.065
Moran’s I among residuals	0.436*** ($p < 0.001$)		-0.042	
R Squared	0.279		0.566	
Akaike info criterion (AIC)	9566.33		8555.55	

- If a p-value is less than 0.05, it is flagged with one star (*). If a p-value is less than 0.01, it is flagged with 2 stars (**). If a p-value is less than 0.001, it is flagged with three stars (***)

- The variance inflation factor (VIF) values for all independent variables used in above regression models were less than 7.5 with percent population without high school diploma had the largest VIF of 4.288, indicating multicollinearity was not a critical concern

- The spatial lag model was not only theoretically more reasonable but justified by the decision rule of spatial regression model selection that involves diagnosis of the statistics of Lagrange Multiplier (lag), Lagrange Multiplier (error), Robust LM (lag), and Robust LM (error) (Anselin, 2005)

eviction in both the city and suburbs of Milwaukee (Desmond et al., 2013; Desmond & Gershenson, 2017; Hepburn et al., 2022). Likewise, several studies suggest a link between elderly populations and eviction (Francis, 2008; Pipal, 2012; Papke, 2021). One study of eviction in San Francisco, Alameda, and San Mateo California found that a disproportionate number of evictions occurred among the elderly and other disadvantaged groups (McElroy, 2018). In relation to mobile home living, existing scholarship at the local level as well as among rural areas of the United States suggest a link between eviction and mobile home living in general (Sullivan, 2017a, b; Lamb et al., 2022; McTavish et al., 2006). Finally, one study of housing insecurity in urban areas found that overcrowding contributed significantly to overall housing insecurity, of which eviction is integral to (Routhier, 2019). Although some suggest that overcrowding can lead to eviction (Harwood & Meyers, 2002; Marcal et al., 2022; Cunneen, 2019), others conversely argue that eviction causes overcrowding (Benfer et al., 2021). Overall, the variety of findings at various geographic scales pertaining to each of these variables, compared to the negative correlations found in our national level study, warrants further investigation into these relationships.

The OLS model explained nearly 28% of the variance of eviction rates as indicated by the Adjusted R Squared statistic (i.e., 0.274 with p-value $<$ 0.001). A statistically significant Moran's I value that measures the degree of spatial autocorrelation among residuals remained an issue that violated the fundamental assumption of random distribution to warrant the use of OLS. Spatially weighted averages of eviction rates were included as an additional independent variable in the spatial lag model to denote the influence of spatial dependence among residuals for nearby observations (the second row in Table 4). The inclusion of the spatial autocorrelation variable that showed significant and positive coefficient effectively improved the model performance reflected by a much larger R squared value than the OLS model (0.566 vs. 0.279). The magnitude of regression coefficients for other predictors normally became smaller after factoring in spatial autocorrelation in regression model. The only exception is disabled population that showed significant and positive sign. Also, the improvement of model performance due to the use of spatial lag model is reflected by a decreased Akaike info criterion (AIC) statistic (from 9566.33 to 8555.55) – the lower the AIC value, the higher the proportion of the variations of the dependent variable being predicted by the explanatory variables in regression.

Conclusion and Discussion

In search of a nuanced understanding of the state of eviction in the U.S. and better understanding of the risk factors associated with eviction rates across U.S. Counties, we first analyzed the disparate patterns of eviction rates across U.S. counties through the lens of USDA urban-rural continuum codes. Then we conducted global and local spatial statistical analyses to reveal the uneven distribution of eviction nationwide and where significantly high and low clustering places (i.e., hot spots and cold spots) are located. Last, we performed multiple linear regression models to explore the associations between county-level eviction rates and CDC generated social vulnerability factors. From this study we report the following three important observations: (1) while evictions are prevalent in populous urban or metropolitan counties, eviction rates can be higher in less-populous outlying counties even non-metropolitan communities. (2) the most striking feature about the uneven distribution of eviction is that hot spots of counties with significantly high rates were largely concentrated in lower Michigan-upper Indiana and the along the east coast that encompasses Virginia, North Carolina, and South Carolina. (3) The spatial regression model explained a moderate degree of the variations of eviction rates across U.S. counties and social vulnerability indicators including (low) income, minority population, single-parent, unemployment rate, apartment living, and low education status were most effective predictors of eviction. As there lacks general consensus as to the scope and magnitude of various factors of eviction at the national level, these results corroborate the findings suggested by several studies in the recent literature especially those conducted at the neighborhood level (Desmond, 2012; Robinson & Steil, 2021; Immergluck et al., 2020; Teresa, 2018).

While our findings of a negative association between per capital income and eviction is understandable given the prevalence of eviction among low-income households (Desmond, 2022), standard definitions for other variables including poverty and group quarters may offer some justification for our findings of a negative association between these variables and eviction. However, existing research on the relationships between eviction and limited English proficiency, persons under 17, persons over 65, mobile home living, and overcrowding add complexity to our findings of negative associations with eviction. We in-turn encourage further research on these relationships.

To the authors' best knowledge, this is the first empirical study examining contemporary patterns of housing eviction rates in the U.S. as well as the spatial relationships between eviction rate and variables from the CDC's Social Vulnerability Index using national datasets. Results of this study provided new information about the remarkable spatial disparities and potential contributing factors of eviction rates, thus enhancing our understanding of the geographic heterogeneity of eviction, a crucial but understudied phenomenon in the U.S. Findings from this study can inform housing reform and public policies with respect to the allocation of resources and mitigation efforts to places where it is most needed. For example, our study revealed that devastatingly high eviction rates and hot spots can be observed not only in large cities and metropolitan areas but also in medium and small MSA counties even nonmetropolitan areas. This finding can influence policies to tackle eviction challenges in medium-sized and small cities, which are often overlooked. Since the publication of sociologist Desmond's *Evicted: Poverty and Profit in the American City* (2016), governments of many large cities have been searching for ways to reduce evictions as eviction can lead to lasting economic devastation for the individuals, families, and communities who experience them. In contrast, governments in less-populated small places are less prepared and lack resources for tackling the eviction crisis.

This article is subject to several limitations. First is about the measure of eviction. The eviction measure we used in this study included only formal court evictions, which is just a fraction of all cases in the pipeline from filing to court indictment that normally takes a long period of time. If using eviction filing rate, the results can be quite different. Second, while commonly used and well-justified, the USDA urban-rural continuum is inherently arbitrary and the population thresholds for classifying communities are modifiable. Therefore, our observations regarding differences among urban-rural locale categories are exploratory and adopting other locale classifications may result in different results. Likewise, the results of the spatial configurations of hot (or cold) spots are sensitive to changes of the spatial parameters for defining spatial weights and band weights of nearby counties and there are other alternative ways for diagnosing spatial clusters. Therefore, the hot spots and cold spots identified in this study are only useful as a screening-level tool to identify areas with extraordinary eviction rates across the country. To get a more holistic understanding of the contours of eviction, additional in-depth investigations using more refined data (e.g., neighborhood-level or individual-level) and comparing different spatial statistical methods with a sensitivity analysis will be plausible. Additionally, we used parametric models in our study, but future studies may benefit from the use of semiparametric models as they have been found to outperform parametric models in measuring and predicting housing outcomes (Bin, 2004).

Third is the about the risk factors used in our regression analysis. Some social vulnerability indicators showed surprising associations with eviction rates (e.g., poverty, people living in mobile homes, crowding, etc.). From another perspective, understanding eviction might rather mean evaluating other potential root causes through an exploration of questions of "power and the political economy dynamics that reside in evictions" (Soederberg, 2018, p. 291). Questions of how land is owned, regulated, financialized, and profited off of may be another productive consideration, especially where land dynamics are intrinsically tied to housing tenure and the potential for eviction (Roy, 2017).

Lastly, the data we used in this study were gathered before the COVID-19 pandemic. Several studies have demonstrated the impactful relationship between eviction and facets of public health (Zewde at al., 2019; Harville et al., 2022; Niccolai et al., 2019), warranting a better understanding of the devastations caused by the unprecedented COVID-19 epidemic nationwide that have dramatically aggravated the existing eviction crisis across communities nationwide, especially the low-income families and communities of color who have been affected the hardest by the pandemic. Future research should therefore analyze data collected in the post-COVID era to investigate the ripple effects of COVID while accounting for other vulnerability measures. Despite the weaknesses, this empirical analysis extends the existing literature by applying innovative geospatial techniques to the analysis of a unique national data set and thus shedding new lights on the spatial heterogeneity of eviction and its risk factors across the U.S.

Declarations

Competing Interests The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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