THE UNIVERSITY OF CHICAGO

Linking Rent Regulation to Housing Quality in New York City 2017-2021

By

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Abstract

This thesis examines the spatial distribution of rent-regulated housing and housing maintenance code violations and explores the spatial spillover effects of rent regulation on property upkeep. It also analyzes changes in housing conditions before and after the implementation of the Rent Law of 2019, which made it more difficult for property owners to deregulate properties. Utilizing spatial clustering and regression analyses of data from New York City, the study reveals: (1) a spatial overlap and clustering of rent-regulated housing and housing maintenance code violations; (2) a negative impact of rent regulation on housing quality that extends beyond individual census tracts to neighboring areas; and (3) potential exacerbation of housing maintenance issues following the enactment of stricter rent regulation laws. These findings suggest challenges of rent regulation policies to balance affordability with quality and that these policies might disproportionately affect low-income households who are vulnerable to displacement and rely on rent regulations for housing stability in gentrifying neighborhoods.

Keywords: Rent Control; Housing Quality; Gentrification; Spatial Cluster; Spatial Regression; Housing Code Violation

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1 Introduction

New York City's housing challenges are emblematic of those faced by many cities in the industrialized world, where the tug-of-war between affordability and quality is a defining feature of the urban housing landscape. Rent regulation policies, designed to ensure affordability, can have unintended consequences that disproportionately affect the living conditions of poorer populations, altering the social and physical fabric of neighborhoods. Previous research has suggested the unintended consequences of rent regulation policies, such as prompting economic repercussions (Epstein, 1988), market misallocations (Glaeser and Luttmer, 2003), and a subsequent reduction in rental supply (Gyourko and Linneman, 1990; Liu et al., 2018). Scholars have also uncovered how landlords circumvent controls, such as deteriorating housing quality, converting or redeveloping properties (Diamond et al., 2019), and harassing or even evicting tenants(Asquith, 2019; Moon and Stotsky, 1993; Ye et al., 2019).

While rent regulation policies aim to protect tenants from displacement and keep housing affordable, its potential to de-incentive landlords to maintain their properties could inadvertently make rent-controlled areas ripe for gentrification, a spatial and social process by which capital investment in the built environment potentially leads to a sociodemographic transformation of a working-class or vacant area of the central city into middle-class residential or commercial use (Davidson and Lees, 2010; Lees et al., 2013; Maloutas, 2012; Wyly and Hammel, 1999), the immigration of affluent households to poorer and lower value areas of the city Atkinson and Wulff, 2009; Patch and Brenner, 2007; Slater, 2017). This research does not assert that rent regulation policies directly cause a deterioration in housing quality. Rather, it identifies an empirical correlation between these policies and specific outcomes in New York City's housing market. By elucidating these correlations, this study aims to enhance understanding of the complexities inherent in rent regulation policies. This approach facilitates an exploration of potential empirical connections between rent regulation and the dynamics of urban housing quality and gentrification, which impact a broad spectrum of populations across the city. This investigation helps frame a more informed discussion on the implications of rent regulation policies without necessarily implying causality.

2 Literature Review

2.1 Rent Regulation and Housing Maintenance

The question of whether rent regulation policies adversely affect housing maintenance is complex and has prompted considerable debate among sociologists, economists, and urban geographers. On one side of the debate, several researchers argue that rent regulation may lead landlords to minimize their investment in maintenance as a strategy to offset the financial restrictions imposed by these policies. This line of argument, supported by the findings of Moorhouse (1972), Albon & Stafford (1990), and Gyourko & Linneman (1990), suggests that rent control mechanisms can indirectly degrade the quality of housing. According to this view, the financial constraints associated with rent regulation create a disincentive for landlords to allocate resources towards the upkeep of their properties, potentially leading to a decline in housing quality over time.

Contrarily, a different strand of the literature challenges this assertion, offering evidence that rent regulation does not necessarily lead to diminished landlord investment in property maintenance. For example, Rydell et al. (1981) and Olsen (1988) argue that the purported negative impact of rent control on maintenance efforts is either overstated or misunderstood. These scholars contend that the effects of rent regulation on property maintenance may be less dire than previously thought because other factors could play a more significant role in determining maintenance levels.

A pronounced concern of economists regarding the relationship between rent control policies and the quality of housing stems from viewing housing as a commodity (Epstein, 1988; Glaeser and Gyourko, 2005; Glaeser and Luttmer, 2003; Topel and Rosen, 1988). Thus, the influence of rent control is usually analyzed through a cost-benefit lens that considers the production and consumption of rent-controlled housing units. For example, Olsen's (1972) analysis of New York City in 1968 estimated approximately 4.4 percent less consumption of housing services by occupants of controlled housing, while 9.9 percent more consumption of non-housing goods than they would in the absence of rent control. This shift resulted in a 3.4 percent increase in real income for rent-controlled households, and poorer families derived greater benefits from rent control compared to wealthier ones. However, the cost imposed on landlords by rent control was identified to be twice the magnitude of the benefit accrued to tenants.

The general consensus among economists is that rent control negatively impacts housing maintenance and quality. For instance, Kearl et al. (1979) demonstrate that more than three-fourths of respondents concurred that rent ceilings detrimentally affect the quality and availability of housing. The negative consequences of rent control on housing maintenance were also emphasized by Arnott (1981). Despite significant advancements in the modeling of housing markets and the empirical study of housing economics, as further explored by Arnott (1995), Olsen (1988), and Rosen (2014; 2021), critiques of rent control continue to be grounded in relatively simplistic models and empirical observations.

Some scholars argue that rent regulation policies might have a neutral impact on housing quality. That is, assuming rent regulation policies are designed to allow landlords to recoup maintenance expenses at market rates, these policies might not inherently discourage landlords from maintaining their properties (Kutty, 1996). This argument is contingent upon the ability of landlords to pass maintenance costs onto tenants without restriction. However, implementing such an ideal scenario is challenging in practice, as seen with the new rent regulation law in New York City (Housing Stability & Tenant Protection Act of 2019), which has closed the loophole that previously allowed landlords to significantly increase rents under the guise of recouping maintenance costs. This change may reduce the flexibility for integrating these costs into controlled rents, potentially creating a disincentive for landlords to invest in property upkeep.

This paper contributes to the ongoing debate about the potential adverse effects of rent regulation policies on housing maintenance through empirical analyses. Specifically, it provides evidence that rent regulation may be inadvertently linked to variations in housing quality across surrounding neighborhoods. By analyzing the spatial distribution and condition of rent-regulated units in relation to their immediate environments, this study illuminates how rent regulation policies might not only impact the directly regulated properties but also influence the broader landscape of housing quality in surrounding areas. This approach aims to broaden the understanding of the effects of rent regulation policies, highlighting their potential to shape urban housing conditions beyond the confines of regulated units.

Additionally, previous economic studies on the impact of rent regulation on housing quality often fail to consider that the lack of incentive for maintenance under rent control might be compounded by an incentive for property deterioration. As explored in greater depth in subsequent chapters of this thesis, which link housing quality to its implications for gentrification, such deterioration can lead to reduced property taxes and tenant displacement. This, in turn, creates vacancies that facilitate the deregulation of controlled properties in some municipalities—a practice that has been made illegal in New York City since 2019.

2.2 Housing Quality and Gentrification Implication

The genealogy of "gentrification" stems from the notion of embourgeoisement, which originally captured the "modernism on the street" of Paris in the late eighteenth century (Harvey, 2003; Pinkney, 1978). Later, Ruth Glass, in her work *Newcomers: The West Indians in London*, published in 1960 coined the term gentrification to describe the influx of middle-income residents, the gentry, to lower-income neighborhoods in London. During that period of time, the accelerating rehabilitation of Victorian Lodging houses, and the tenurial transformation from renting to owning houses, alongside property price increases, led to the displacement of working-class occupiers by middle-class incomers (Slater, 2021). By the 1970s, gentrification proliferated as the advanced capitalist world experienced a dramatic loss of manufacturing jobs and a parallel increase in the service industry.

Propped up by a series of neoliberal policies of deregulation, marketization, and privatization of housing and urban services, gentrification as a distinct process of urban ascents in the dis-invested inner-city neighborhoods by pioneer gentrifiers, public or private alike, becomes ubiquitous in cities of the post-capitalist world (Fainstein and Campbell, 2016; Smith, 2005). Today, gentrification is generally defined as simultaneously a spatial and social process whereby capital investment in the built environment potentially leads to a sociodemographic transformation of a working-class or vacant area of the central city into middle-class residential or commercial use (Davidson and Lees, 2010; Lees et al., 2013; Maloutas, 2012; Wyly and Hammel, 1999), the in-migration of affluent households to poorer and lower value areas of the city (Atkinson and Wulff, 2009; Patch and Brenner, 2007; Slater, 2017). Atkinson and Wulff, 2009; Patch and Brenner, 2007; Slater, 2017)

Urban geographers and sociologists have examined ways to measure gentrification and displacement quantitatively. Spatial diversification, segregation, and variation and the innate theoretical complexity of gentrification as a sociological phenomenon make the development of a methodologically sound measurement of gentrification challenging Holm and Schulz, 2018). Debates concerning residential population displacement in the context of gentrification remain vociferous but are hampered by a lack of empirical evidence of the extent of the displacement occurring. This implies that whilst the quantitative study of displacement remains difficult, patterns and processes of displacement can be inferred through existing data sources, as well as data generated from those who themselves have experienced displacement (Easton et al., 2020; Sims, 2021).

Housing maintenance can play a crucial role in signaling the gentrification process under the Rent Gap Theory. Among the many still heavily contested causes of gentrification in the scholarship of urban study, Neil Smith's (1979) Rent Gap Theory is a prevailing framework developed to explain the initiation of gentrification. Smith's Theory argues that the return of capital from the suburbs to the city drives gentrification—the restructuring of capital shifts land values and housing (re)development. A more straightforward explanation of the Rent Gap Theory is the gap between the current price of investing in a house and the potential price of this house after the landlord renovated it. In other words, a Rent Gap would occur if the future rental price becomes higher than the current investment price. Therefore, if the Gap is wide enough, gentrification could be initiated as a type of profit margin maximization (Smith, 1987, 2005).

Under the Rent Gap Theory, owners of rent-regulated housing are motivated to deregulate their properties to capitalize on potentially higher rental profits. This can be achieved either by selling to a developer who anticipates higher returns or by renovating the property to increase current rental income. Until 2019, Rent Laws allowed owners to deregulate properties after a period of vacancy, incentivizing strategic disinvestment from rent-regulated properties. This disinvestment serves dual purposes: 1) Property deterioration can lower its valuation, reducing property taxes and attracting buyers looking to capitalize on the Rent Gap; 2) Deterioration can also drive out current tenants, leading to vacancies that qualify the property for deregulation, thereby enabling future profit increases. By reducing current investments and increasing future rental prices, owners can effectively widen the rent gap, encouraging capital influx aimed at ”buying low and selling high,” maximizing potential profits.

The Rent Gap Theory posits that capital investments are more likely to occur in lower-income, not yet gentrified areas where the potential for profit is higher, as the primary goal for capitalists is to widen the rent gap and maximize future rental income. This idea aligns with the concept of the city as a ”growth machine” (Logan et al., 1987), suggesting that areas benefiting from government incentives such as tax abatements or development subsidies are particularly attractive for capital investment, setting the stage for gentrification (Slater, 2017; Smith, 2005).

Moreover, areas undergoing gentrification often exhibit a cycle of urban decay and housing deterioration. Such deterioration not only signals the onset of capital inflow but also serves as a precursor to the potential for gentrification. This cycle indicates that before the inflow of investments, physical and economic decline in these areas may actually stimulate interest among investors looking to capitalize on the widening rent gap (Smith, 1987, 2005).

This thesis is motivated in part by the literature examining the relationship between the progression of gentrification, housing quality, and rent regulation. Investigating rent regulation in relation to housing quality within urban spaces could offer a novel approach to understanding the dynamics of capital and population flows that shape the social geography of gentrification. Furthermore, an exploration of how rent regulations and housing quality interact could illuminate the behaviors of landlords and tenants in gentrified areas. This thesis employs a quantitative and spatial analytic approach to test various claims made by urban geographers and sociologists about gentrification. Specifically, it seeks to determine how rent regulation in New York City—often viewed as a potent safeguard against gentrification—may inadvertently produce adverse consequences for lower-income households in gentrifying neighborhoods. This analysis aims to provide empirical support for understanding the complex interplay of these factors in urban transformation.

2.3 Hypotheses

This thesis investigates the spatial patterns of housing maintenance code violations and the net loss of low-income households, examining their association with the prevalence of rent-regulated housing across New York City boroughs from 2017 to 2021. The study is guided by three hypotheses: First, it posits that maintenance code violations and rent-regulated housing are not randomly distributed, but instead are likely to be spatially clustered and overlapping. This suggests a geographic concentration of housing quality issues within areas of rent regulation. Second, this research hypothesizes that there is a significant association between the prevalence of maintenance code violations and rent-regulated housing, potentially influenced by spatial spillover effects where the conditions in one location can affect adjacent areas. Lastly, the study anticipates that the enactment of more stringent rent control laws in 2019 has led to an increase in the prevalence of maintenance code violations, indicating that policy changes may have unintended consequences on housing maintenance.

3 Data

Subsequent analyses utilize three primary data sources: housing maintenance code violations sourced from New York City's OpenData portal; Rent Controlled Housing information obtained from the Rent Guideline Board of New York City, and records acquired through FOIA requests from the New York State Department of Community Housing Renewal (DCHR) prior to 2019; and the American Community Survey (ACS) five-year estimates spanning 2017 to 2021. All datasets are geo-referenced and mapped to a shapefile of the

New York City Census Tracts for the year 2020.

3.1 Housing Maintenance Code Violation

The Department of Housing Preservation and Development (HPD) issues violations for conditions in rental dwelling units and buildings that contravene the New York City Housing Maintenance Code (HMC) or the New York State Multiple Dwelling Law (MDL). Each row in the dataset represents a specific violation under these regulations. Violations are categorized into four classes: Class A (non-hazardous), Class B (hazardous), Class C (immediately hazardous), and Class I (information orders).

The selective enforcement practices and systemic biases observed in housing inspections represent significant limitations of this housing violation data. Research has shown that inspectors often uphold middle-class property values and preferences, which can lead to discriminatory practices against lifestyles and businesses that deviate from White middle-class norms in cities like Toronto, Philadelphia, and New York City (Fairbanks, 2009; Madden and Marcuse, 2016; Novak, 1996; Valverde, 2011). Additionally, there is a demonstrated bias in inspections that tends to overlook violations affecting low-income and minority communities, which can exacerbate vulnerabilities during disasters and diminish the overall quality of life (Desmond and Shollenberger, 2015; Harcourt, 2001; Klinenberg, 2003; Sampson and Raudenbush, 2004; Satter, 2009). Despite the inherent biases in housing violation data, it remains the most comprehensive source available for studying urban housing conditions across a large geographical area like New York City. The richness of the data allows for observing significant variance even under biased conditions, providing the depth needed to yield meaningful results and insights into urban housing quality that no other data source could match. In later analysis, this thesis included demographic, geographic, and economic controls to increase the robustness of the results.

For the subsequent spatial analysis, this study constructed a spatially intensive variable at the census tract level—housing maintenance code violations per 1,000 households – using data from 2017 to 2021. This process involved selecting only the hazardous (Class B) and immediately hazardous (Class C) violations and aggregating this data according to the census tracts where they occurred. This measure provides a detailed perspective on the density of critical housing code violations within distinct geographic areas.

3.2 Rent Regulation Data

The dataset on Rent Regulated Units was compiled from documents sourced from the Rent Guideline Board of New York City in 2022 and records obtained through FOIA requests from the New York State Department of Community Housing Renewal (DCHR) before

2015. It contains detailed information on the location and distribution of rent-regulated properties throughout New York City.

Rent-regulated buildings in New York generally adhere to specific criteria: they house six or more units, were constructed before 1974 (with exceptions for newer buildings receiving tax exemptions), and are not co-ops or condos. Despite this, not all apartments within these buildings remain rent-stabilized indefinitely. From 1993 until June 13, 2019, a legal provision allowed for the deregulation of apartments whose rents surpassed certain thresholds. These thresholds escalated progressively: \$2,000 for leases initiated between 1993 and June 23, 2011; \$2,500 from June 24, 2011, to June 14, 2015; \$2,700 from June 15, 2015, to December 31, 2017; \$2,733.75 throughout 2018; and \$2,774.76 from January 1, 2019, to June 13, 2019 (NYC Rent Guidelines Board).

Due to numerous units being deregulated between 2017 and 2019, this study enhanced the official dataset with FOIA-obtained records from the New York State Department of Housing and Community Renewal (DHCR), which may still include some units deregulated prior to 2022. Additionally, using the Borough Block Lot (BBL) code for each rent-controlled address, I scraped data from the New York City Department of Buildings' information portal (DOB Now NYC) to determine the maximum potential number of rent-controlled units at each address. This dataset has limitations, such as the inability to confirm the exact number of units at each rent-regulated address and the reliance on voluntary landlord reports, which may not fully account for deregulated units over time. However, this dataset does provide an upper estimate of the number of rent-regulated addresses and units.

For the subsequent spatial analysis, this thesis constructed a spatially intensive variable at the census tract level—the number of rent-regulated units per 1,000 households—providing a measure of rent regulation density within specific geographic areas.

3.3 Household Income and Housing Data

Sourced from the American Community Survey (ACS) five-year summaries for 2017 to 2021 via the Census API, the analysis included key demographic and economic indicators to examine the relationships between housing deterioration and gentrification across New York City. The dataset encompasses the total number of households, total population, median household income, households below the poverty level, median gross rent, and the proportion of severely rent-burdened households. Additionally, it captures the distribution of households by income levels, specifically those below 30% of the Area Median Income (AMI), those between 30-50% AMI, and those between 50-80% AMI. The inclusion of these AMI variables is justified as studies have found that households earning under 80% of the AMI account for 98% of the rent-burdened households in New York City (AMI Fact Sheet, Association for Neighborhoods and Housing Development).

3.4 Shapefile and Spatial Weights

Sourced from OpenData NYC, a New York City government data portal, the shapefile—a popular geospatial vector data format for GIS software used to store location, shape, and attributes of geographic features—was cleaned by excluding census tracts with no residents, and tracts used for non-residential purposes such as train yards, prisons, parks, and cemeteries.

In the spatial analysis of New York City, the study generated a spatial weight matrix using binary weights and first-order Queen contiguity using the New York City Census Tract 2020 Shapefile. Binary weights assign a value of 1 to pairs of observations that are defined as neighbors and a value of 0 to all others, simplifying the representation of spatial relationships. Figure 1 demonstrates the concept of first-order Queen contiguity, which stipulates that census tracts are considered neighbors if they share at least one vertex (corner point), as illustrated in the context of Lower Manhattan.

This spatial weighting scheme is crucial for quantifying the geographical relationships between observations in the dataset. It allows for the modeling of spatial auto-correlation, where the housing quality or violation status in one census tract is potentially influenced by the same characteristics in neighboring tracts

4 Method and Results

This thesis adopted a forward specification approach, where each method builds upon the previous to test increasingly specific hypotheses. Initially, the paper employed a Spatial Clustering algorithm to identify spatial patterns of concentration overlaps between rent regulation and violation variables. Subsequently, it utilized a series of spatial regression models to examine the spatial dependencies among these variables. Finally, the study conducted a non-spatial difference-in-differences analysis to provide some causal inferences. This analysis used rent regulation as the treatment variable and the enactment of the 2019 rent law as the intervention. The aim was to determine whether the combination of rent regulation and stricter rent law led to an increase in violations recorded.

4.1 Spatial Clustering

4.1.1 Detect Clusters through Spatial Auto-correlation using Moran's I

This study examined the spatial distribution and clustering of housing maintenance code violations and rent-regulated housing across New York City. A fundamental concept em-

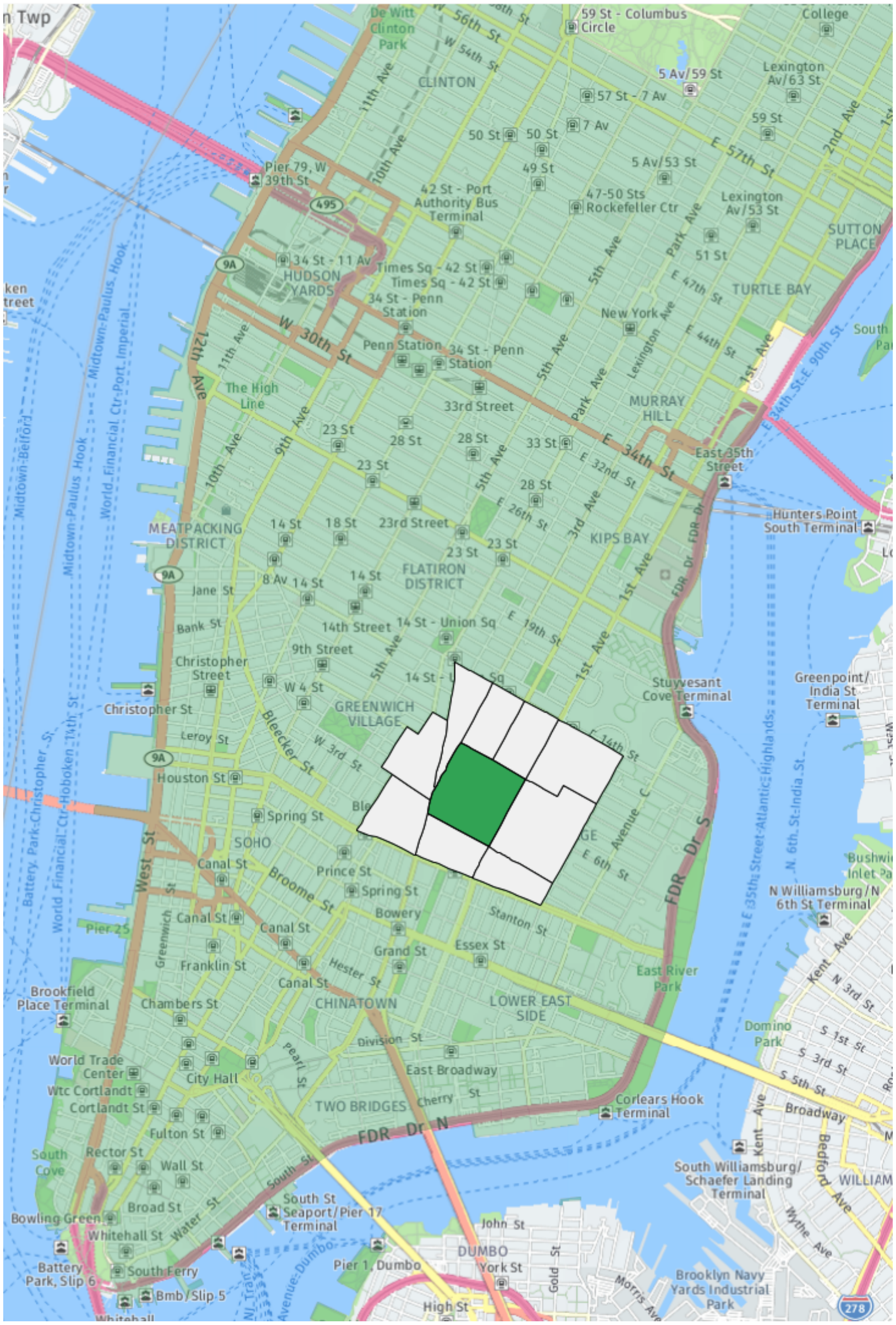

Figure 1: Census Tracts(White) are neighbors of Census Tract(Green) under the First Order Queen Contiguity

ployed to detect and quantify spatial patterns is spatial auto-correlation, which measures the correlation of a variable with itself across space. Essentially, the clustering algorithm determines whether nearby or neighboring locations exhibit similar (or dissimilar) values, serving as a test of whether the spatial pattern of a phenomenon is random, clustered, or dispersed.

Univariate Moran's I was utilized as a statistical tool specifically suited to detect these patterns. It provides a single summary measure of spatial auto-correlation for a variable across the study area. In essence, it is a cross-product statistic between a variable and its spatial lag, with the variable expressed in deviations from its mean. For an observation at location i, this is expressed as $z_i = x_i - \bar{x}$, where $\bar{x}$ is the mean of variable x. Moran's I statistic is then:

$$I = \frac{\sum_i \sum_j w_{ij} z_i z_j / S_0}{\sum_i z_i^2 / n}$$

with w_{ij} as the elements of the spatial weights matrix, $S_0 = \sum_i \sum_j w_{ij}$ as the sum of all the weights, and n as the number of observations (Anselin, 1996).

In the context of this study, positive Moran's I value suggests clustering of similar values, indicating areas with either high incidences of maintenance code violations or a high density of rent-regulated housing. Conversely, a negative value indicates dispersion, where values are dissimilar and spread out across the area.

4.1.2 Spatial Clustering Setup

The primary hypothesis of this study asserts that housing code violations and rent-regulated units are not randomly dispersed but are instead clustered within specific urban areas of New York City. To evaluate this hypothesis, the research employs Univariate Moran's I statistics in two distinct forms: (1) Global Univariate Moran's I, which assesses spatial autocorrelation across each borough to determine how attributes such as code violations or rent-regulated units are spatially correlated among census tracts; and (2) Local Univariate Moran's I, also known as a type of Local Indicators of Spatial Association (LISA), which identifies and visualizes specific spatial patterns and concentrations of these attributes.

The analytical process initiates with the calculation of Global Univariate Moran's I for the key attributes—housing maintenance code violations and rent-regulated housing. This involves the inclusion of a spatial weights matrix to model the spatial relationships among the observational units, which are census tracts as specified in Section 3.4. Using the spatial weight matrix, the Moran's I statistic is computed to assess the degree of spatial clustering. If significant spatial clustering is detected, the analysis progresses to identify the specific locations of these clusters using Local Moran's I.

4.1.3 Spatial Patterns of Housing Maintenance Code Violations and Rent Regulated Housings are Clustered

To investigate whether the density of Housing Maintenance Code Violations and rent-regulated housing are clustered or randomly distributed across New York City, the study employs Global Moran's I statistical tests. This metric gauges the overall degree of spatial auto-correlation for the study area and provides a single summary measure indicative of spatial clustering within the city (Anselin, 1996; Anselin et al., 2000). This is part of the forward specification for clustering analysis. Such an analysis is the first step in clustering analysis, designed to ascertain the presence of clustering before pinpointing its specific geographic locations.

The Global Moran's I statistics indicate significant spatial clustering for all examined variables in New York City: serious house maintenance code violations issues (0.7112, p-value: 0.001) and rent-regulated housing (0.5037, p-value: 0.001). These results suggest we reject the null hypothesis that the patterns of code violations and rent-regulated units are randomly distributed. In addition, the positive values of Moran's I statistics of each variable suggest code violations and rent-regulated housing are clustered.

4.1.4 Local Univariate Moran's I to Identify Clusters Locations of Housing Maintenance Code Violations and Rent Regulated Housings

The Global Univariate Moran's I is a measure of global spatial auto-correlation and provides a single summary statistic for the whole study area, but the Local Univariate Moran's I extend this by providing a local statistic for each cluster location, thus revealing the local structure of the data. Since the previous Section found evidence of spatial autocorrelations in the spatial distribution of rent-regulated housings and housing maintenance code violations leveraging Global Univariate Moran's I, we move on to identifying the locations and spatial overlaps of rent-regulated housing clusters and housing maintenance code violations are clustered using the Local Moran's I.

Local Moran's I principles are an extension of the Global Moran's I statistics. The Local Moran statistic was suggested in Anselin (1996) as a way to identify local clusters and local spatial outliers. A corresponding *Local* Moran statistic would consist of the component in the double sum that corresponds to each observation i, or:

$$I_i = \frac{\sum_j w_{ij} z_i z_j}{\sum_i z_i^2},$$

In this expression, the denominator is fixed and can thus further be ignored. For notational simplicity, we replace it with c so that the Local Moran expression becomes $c.\sum_j w_{ij} z_i z_j$. After some rearranging, we obtain the expression:

$$I_i = c.z_i \sum_j w_{ij} z_j,$$

or, the product of the value at location i with its spatial lag, the weighted sum of the values at neighboring locations (Anselin, 1996).

In this study, the Local Moran's I statistic is applied to each census tract for two specific variables: Housing Maintenance Code Violations and Rent Regulated Units. The purpose is to detect areas with significant spatial clustering. Clusters of high values, termed "High-High," indicate a census tract with many violations is surrounded by tracts with similarly high numbers. Conversely, "Low-Low" clusters represent areas with few Rent Regulated Housing units, neighbored by tracts with similarly low counts. "High-low" areas are those where a tract with high values is encircled by tracts with low values, and "Low-High" areas are the opposite. For instance, a "High-High" Code Violation cluster signifies a dense area of tracts, each with a high number of code violations, indicative of a broader regional issue. Meanwhile, a "Low-Low" Rent Regulated Housing cluster signifies a region where tracts uniformly exhibit a scarcity of rent-regulated units.

The analysis of Local Moran's I across various boroughs reveals consistent spatial patterns in housing violations, indicating that hotspots of violations are recurrent and closely tied to geographic, neighborhood, and demographic characteristics. Despite variations in the overall intensity of violations as depicted on Choropleth maps (see, for example, Figure 2 and Figure 4), the concentration of auto-correlations remains stable over the years, underscoring the persistence of specific clusters. Particularly, the correlation between cluster types and the socioeconomic status of census tracts is stark. For instance, in Manhattan (see Figure 3), areas like the Upper East Side consistently exhibit superior housing quality compared to the lower-income neighborhoods of Harlem, which demonstrate higher levels of violations. This pattern is not unique to Manhattan but is similarly observed in Brooklyn (see Figure 5) and Queens (see Figure 7, where wealth disparities within census tracts significantly influence the quality of housing. Such findings underscore the critical impact of economic factors on urban housing conditions, suggesting a targeted approach in policy-making to address these entrenched spatial disparities.

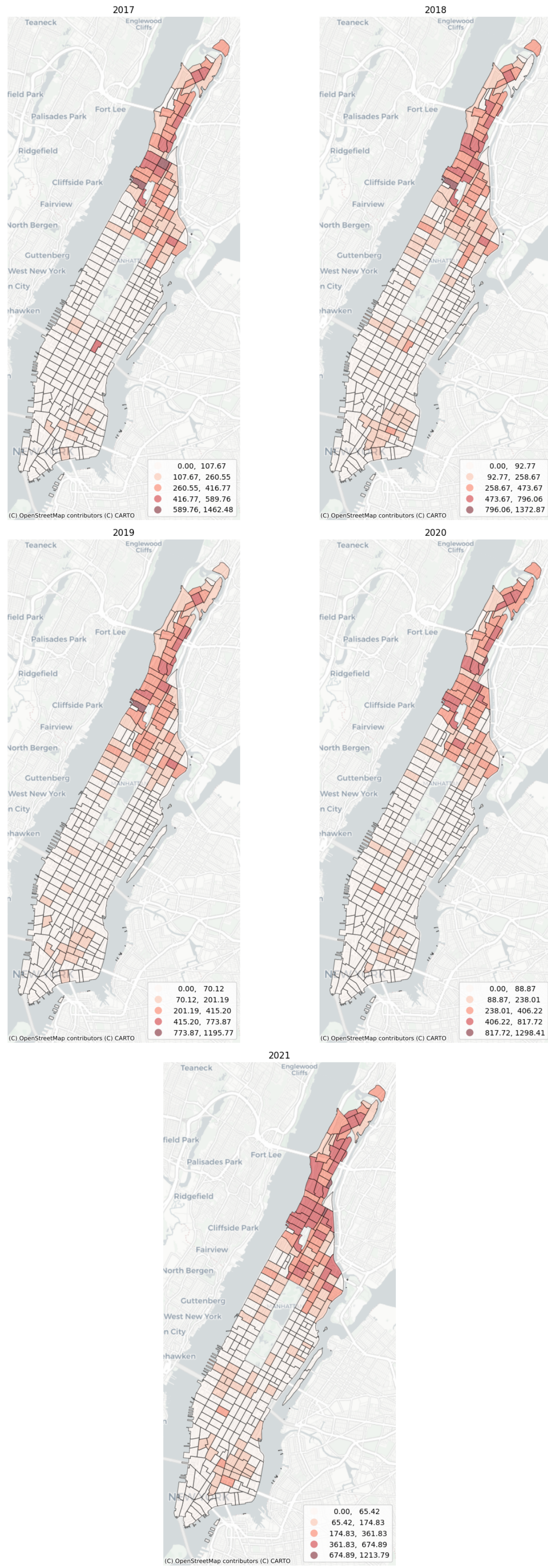

Figure 2: Manhattan: Intensity of Housing Maintenance Code Violations 2017-2021

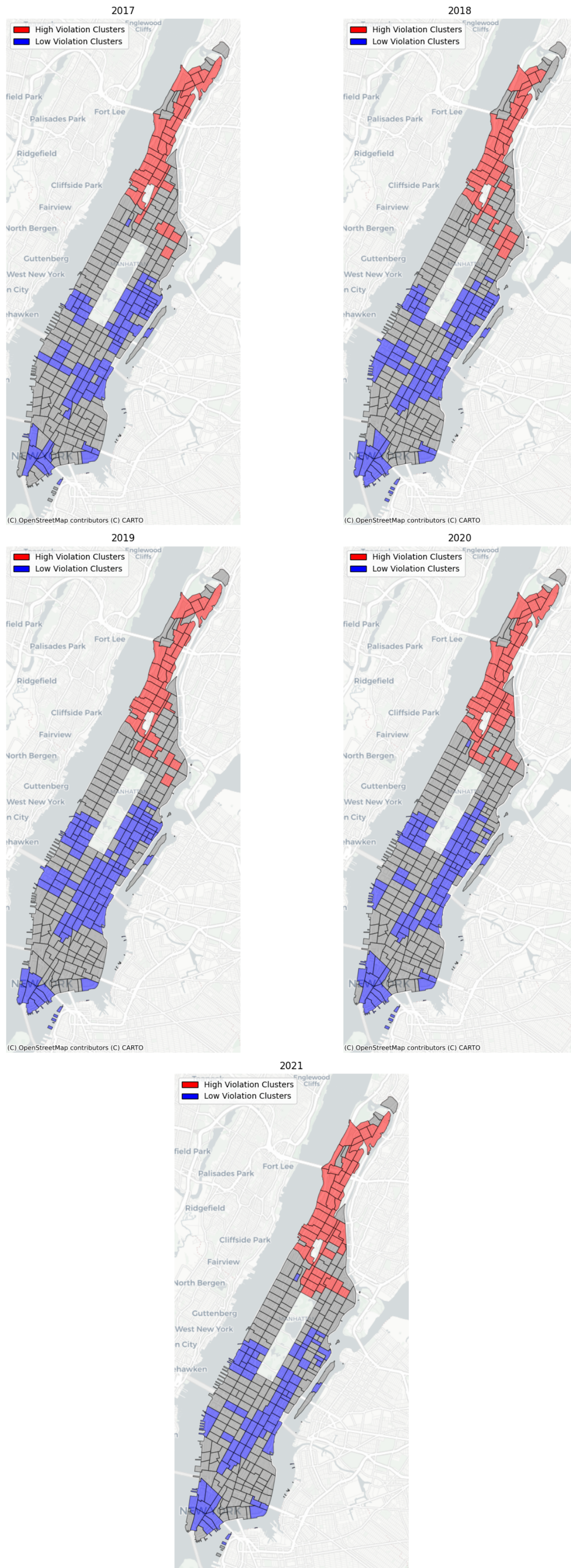

Figure 3: Manhattan: Clusters of Housing Maintenance Code Violations by LISA 2017-2021

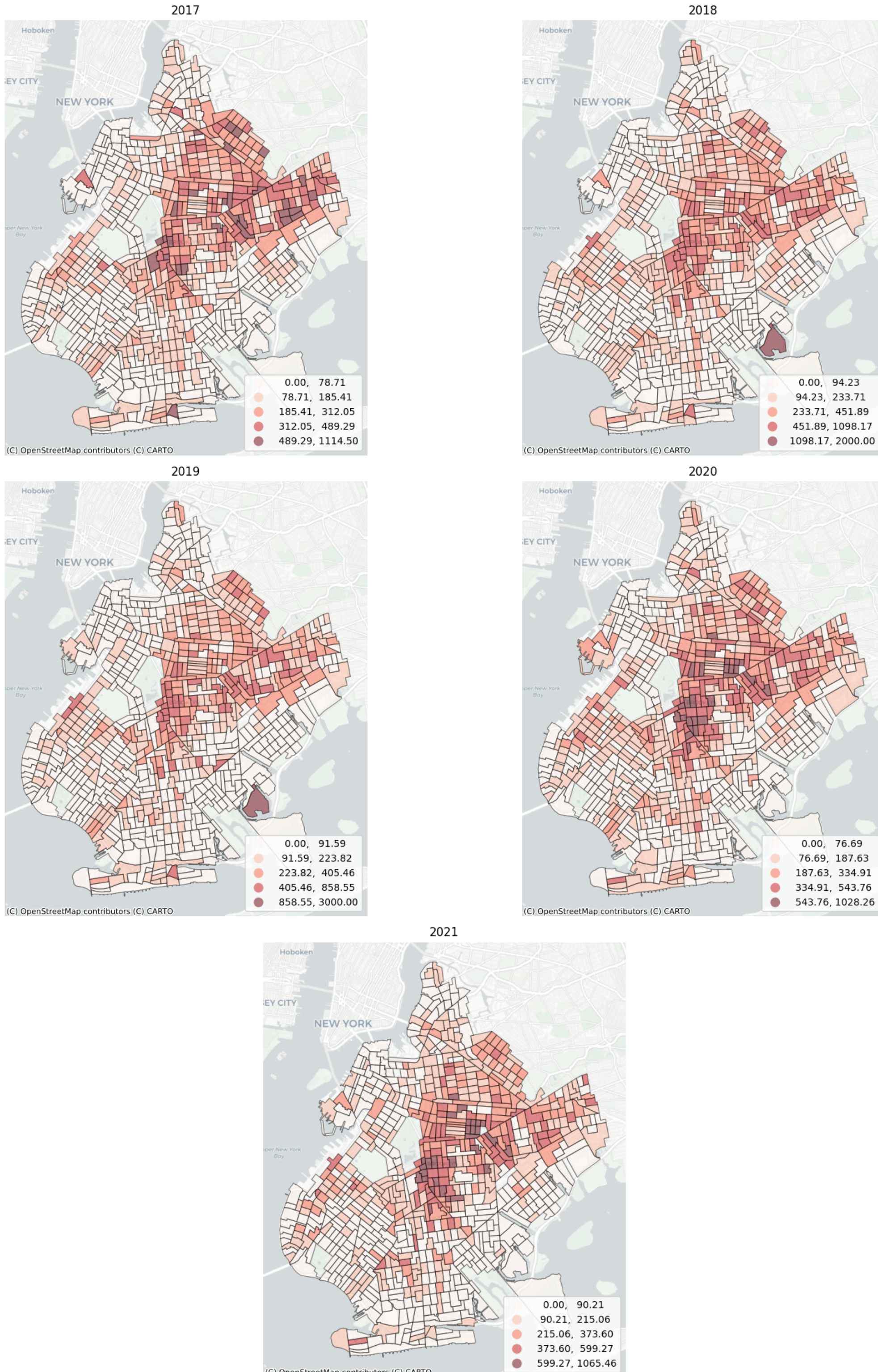

Figure 4: Brooklyn: Intensity of Housing Maintenance Code Violations 2017-2021

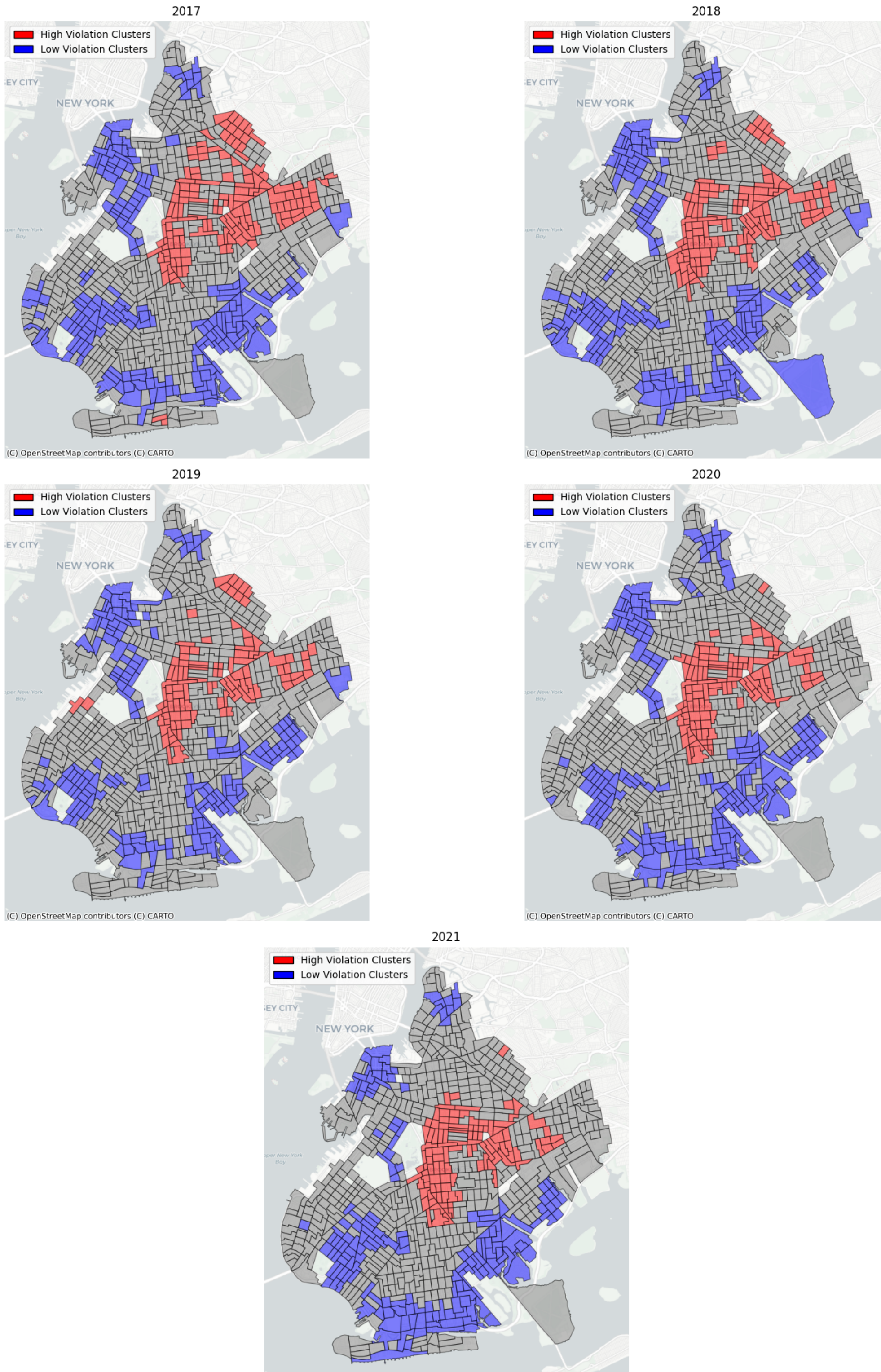

Figure 5: Brooklyn: Clusters of Housing Maintenance Code Violations by LISA 2017-2021

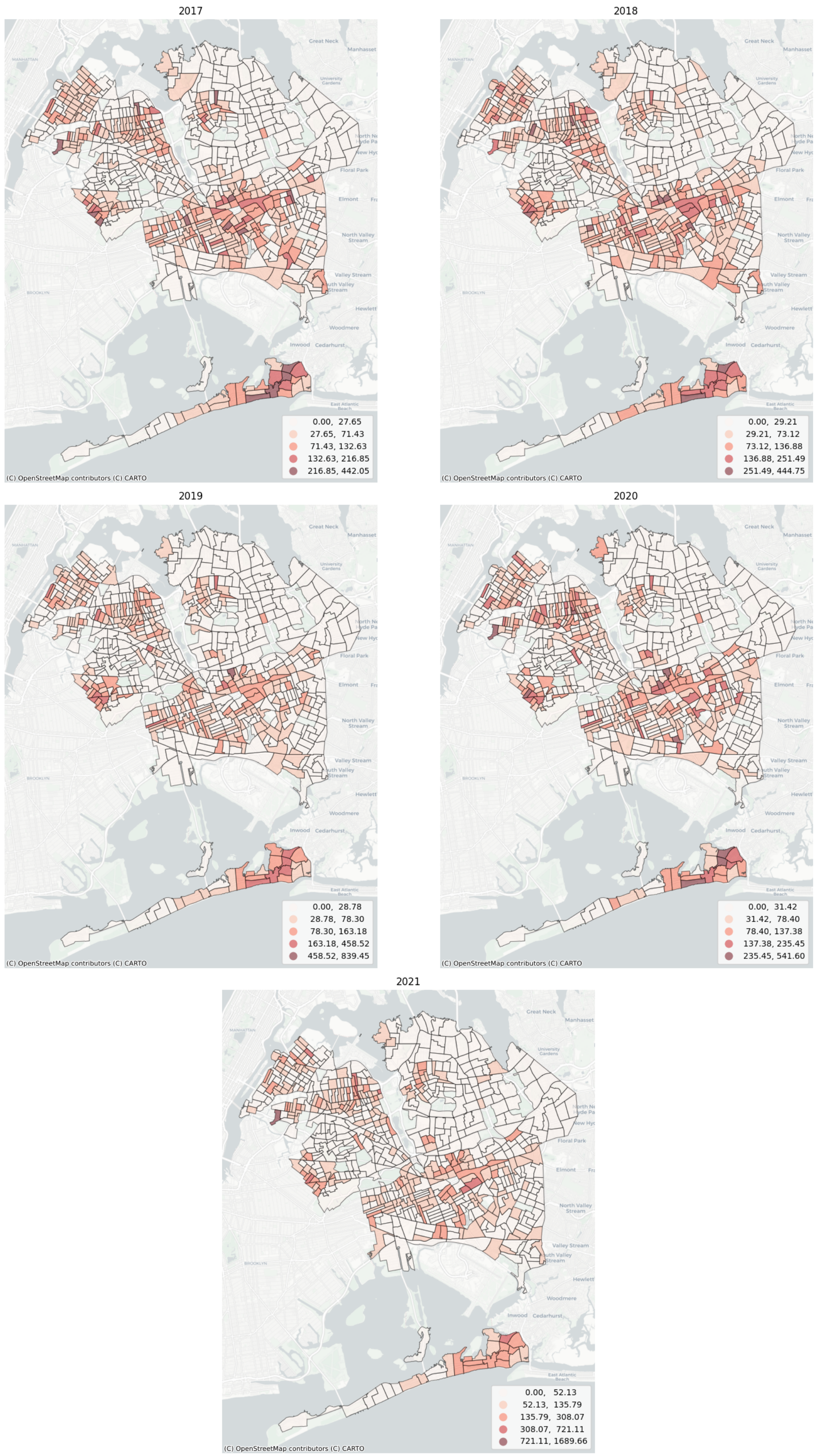

Figure 6: Queens: Intensity of Housing Maintenance Code Violations 2017-2021

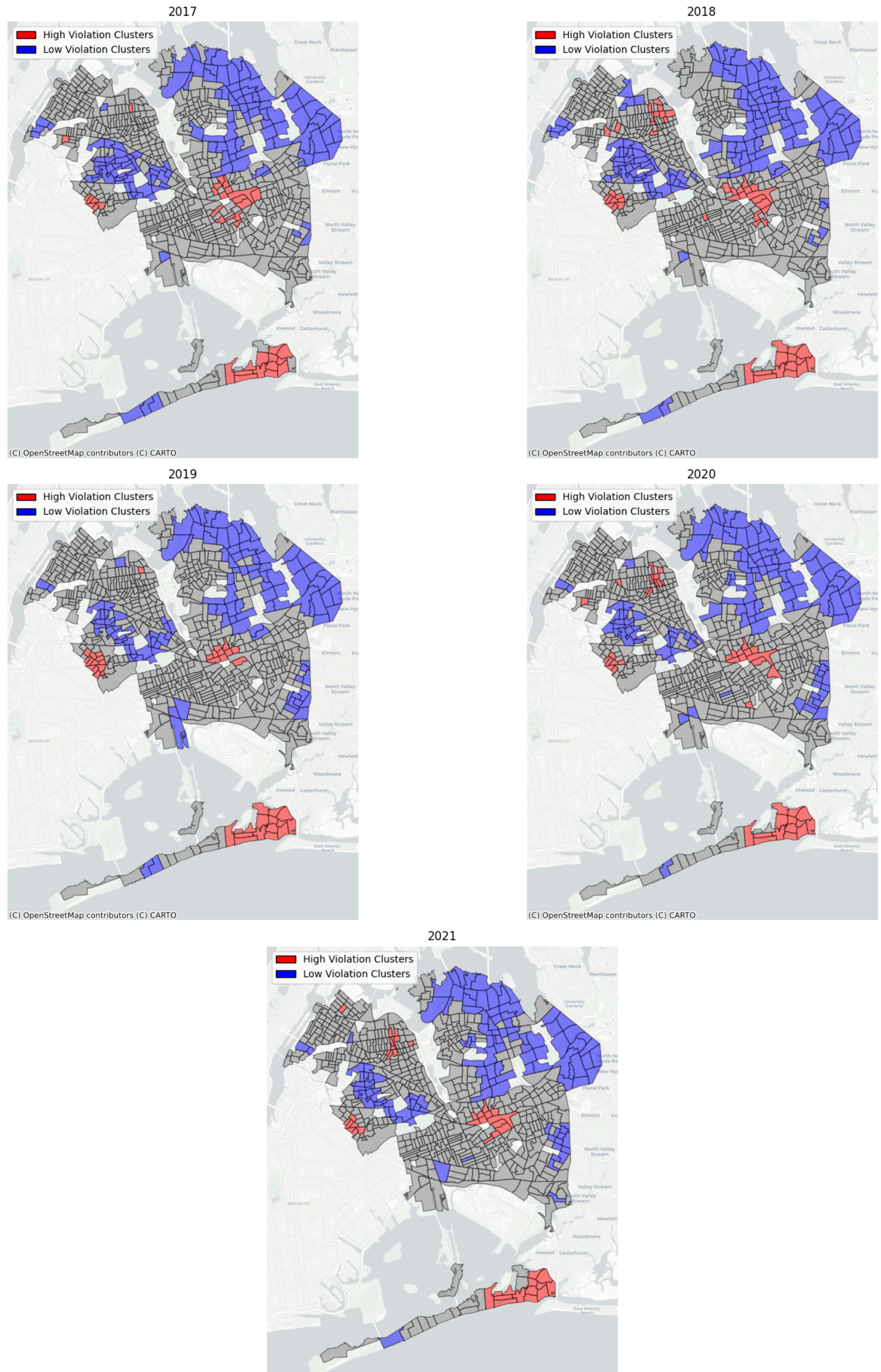

Figure 7: Queens: Clusters of Housing Maintenance Code Violations by LISA 2017-2021

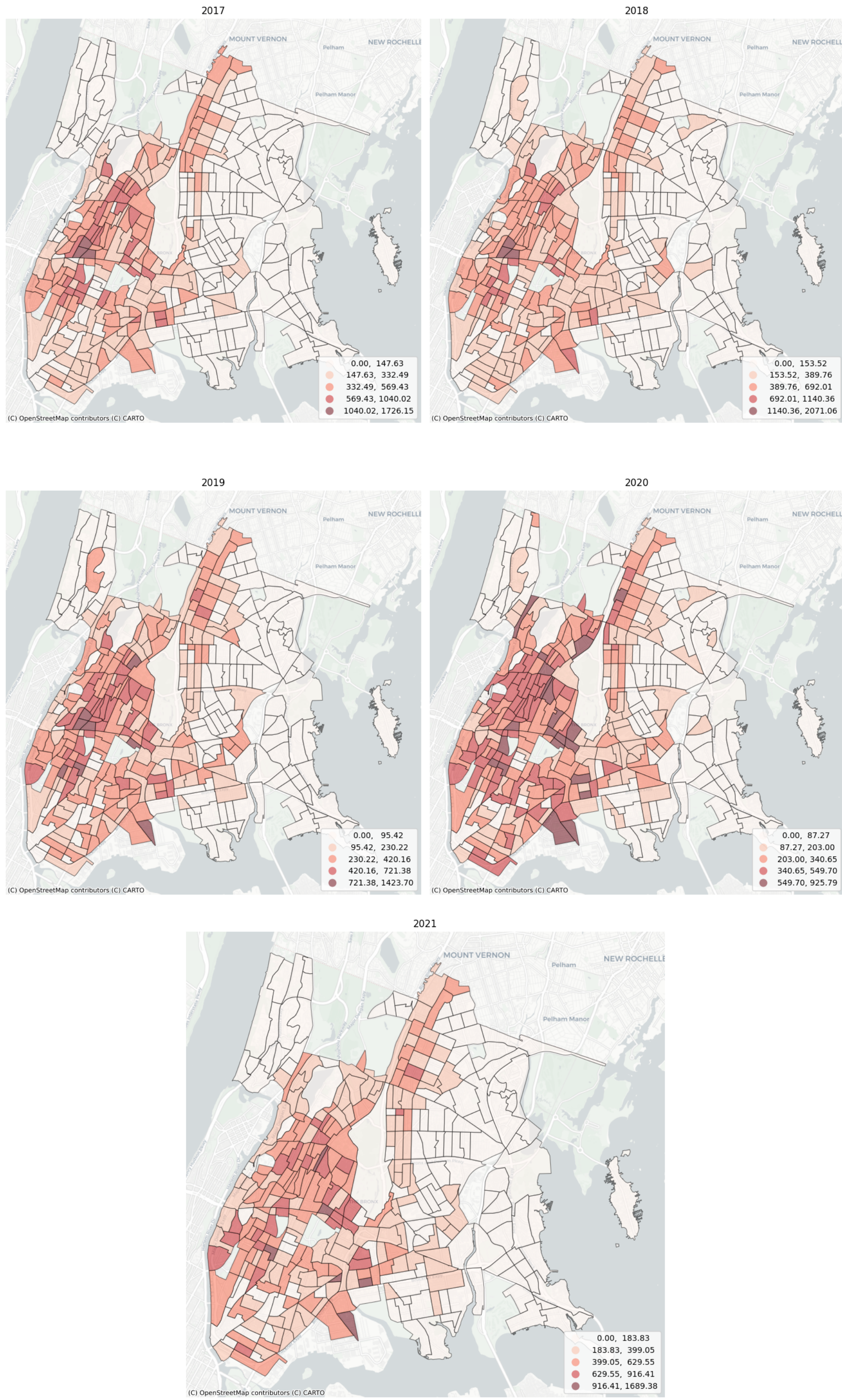

Figure 8: Bronx: Intensity of Housing Maintenance Code Violations 2017-2021

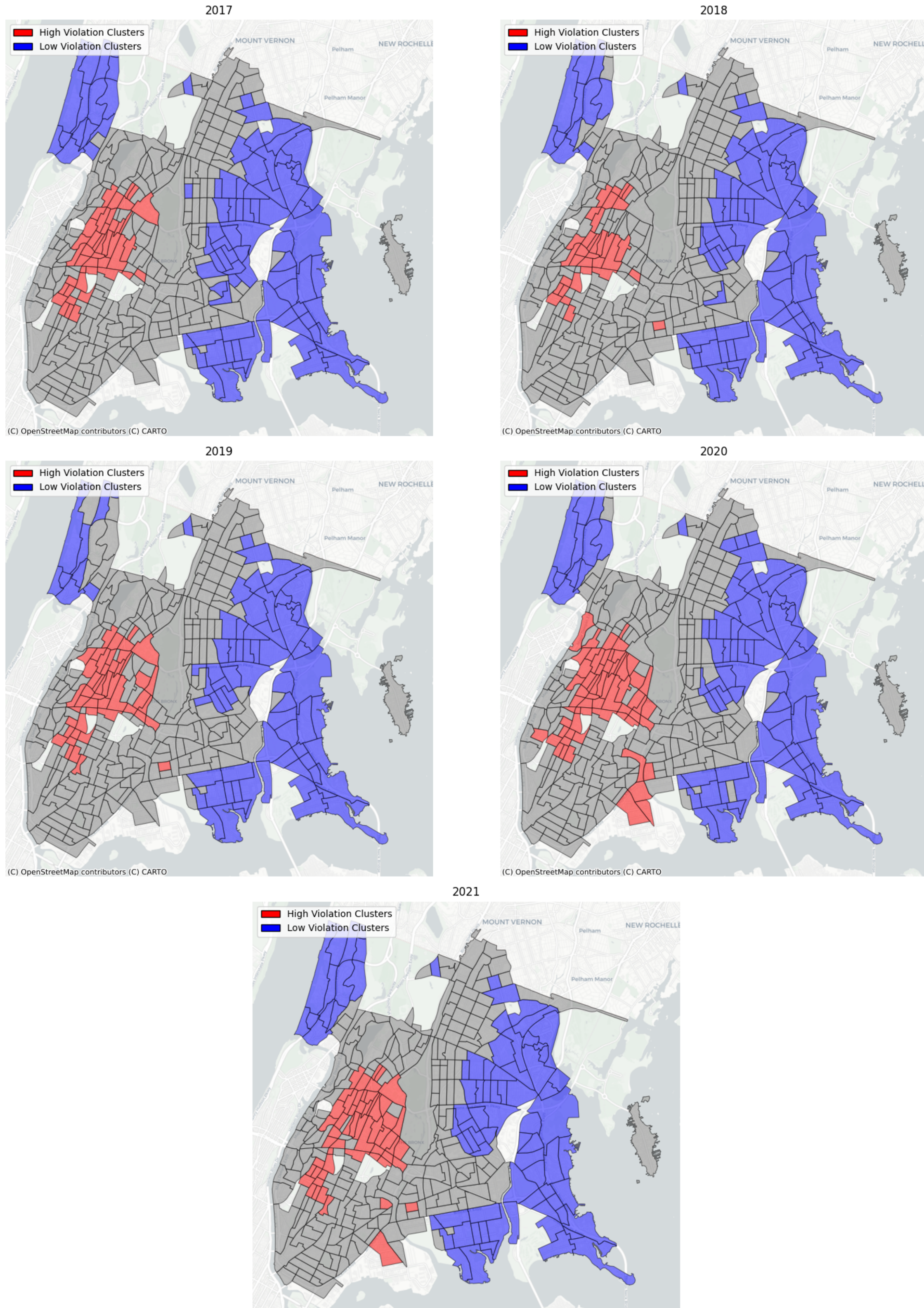

Figure 9: Bronx: Clusters of Housing Maintenance Code Violations by LISA 2017-2021

4.1.5 Overlapping Clusters Locations of Housing Maintenance Code Violations and Rent Regulated Housings

Having identified clusters for Housing Maintenance Code Violations and Rent Regulated Housing units, the study progresses to a spatial overlay analysis. Here, the clusters classified as "High-High" for both variables are superimposed to pinpoint areas exhibiting simultaneous high occurrences of both issues.

The results from the LISA overlays demonstrate that neighborhoods with lower concentrations of rent-regulated units are likely to have fewer housing quality issues. In contrast, areas with more rent-regulated housing face greater challenges with housing deterioration. The predominance of Low-Low Clusters compared to High-High Clusters suggests that the absence of rent regulation correlates more strongly with better housing quality than does the presence of rent regulation with poorer housing conditions.

High-High Clusters Overlap: Indicates that 26.32% of areas with dense rent-regulated units also report high housing violations.

Low-Low Clusters Overlap: Reveals that 65.07% of neighborhoods with low rent-regulated units have minimal housing violations. This suggests fewer rent-regulated units have better housing quality in areas.

The LISA (Local Indicators of Spatial Association) analysis, illustrated in Figure 10, examines the spatial correlation and clustering of maintenance code violations alongside rent-regulated housing. This analysis is crucial for testing the hypothesis that these variables are not merely clustered, but also exhibit significant spatial correlation. By overlaying the High-High clusters from both datasets, the study pinpoints areas where these clusters intersect. As presented in Table 1, the overlapping zones predominantly fall within low-income neighborhoods and communities of color, which also report high poverty rates. This finding suggests a significant concurrence of rent-regulated housing with elevated rates of maintenance code violations in these areas, underlining the spatial dimensions of housing challenges in these communities.

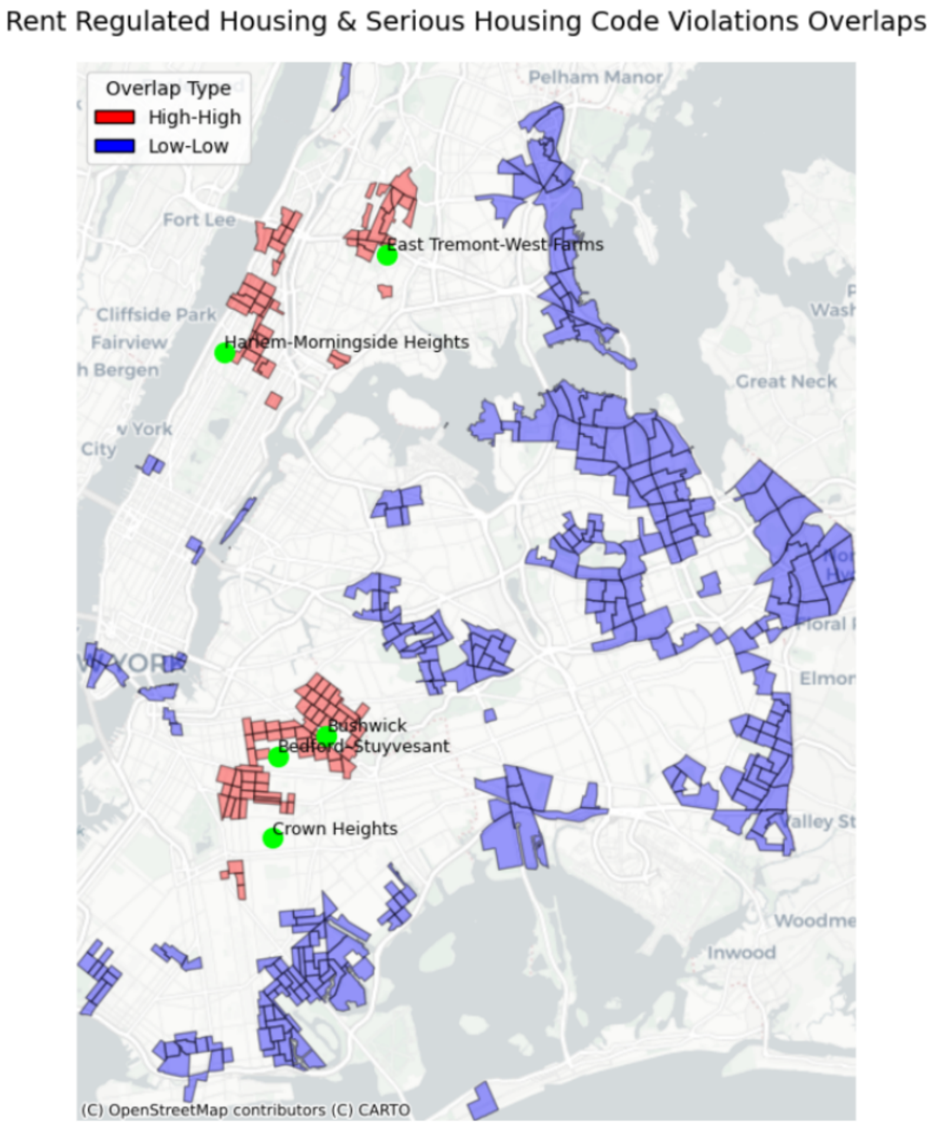

Figure 10: Univariate LISA Overlaps of Rent Regulated Units and Serious Code Violations

Neighborhood	Racial Composition	Poverty Rate
Bushwick	Hispanic: 51.8% Black: 15.5% Asian: 5.9% White: 23.0%	24.2%
Bedford-Stuyvesant	Hispanic: 18% Black: 47% Asian: 4% White: 26%	24.2%
Harlem-Morningside Heights	Hispanic: 27.0% Black: 44.2% Asian: 3.9% White: 17.5%	28.4%
East Tremont-West Farms	Hispanic: 66.1% Black: 30.1% Asian: 1.0% White: 1.2%	38.6%

Table 1: Demographic and Economic Overview of Select Neighborhoods with Clusters of High Rent Regulated Housing and Maintenance Code Violations (NYC Housing and Neighborhood Data, NYU Furman Center)

4.2 Spatial Regression

The previously conducted univariate clustering analysis independently assessed Housing Maintenance Code Violations and Rent Regulated Housing, without directly exploring the statistical relationship between these two variables. This analysis revealed a significant overlap in their spatial distributions, suggesting a potential interconnection. This intersection provides a foundation for a more sophisticated spatial regression analysis, which this section will undertake. The analysis aims to test the hypothesis that Maintenance Code Violations are associated with the prevalence of Rent Regulated Housing, and that such associations are subject to spatial spillover effects. For this purpose, Rent Regulated Housing is posited as the independent variable and Housing Maintenance Code Violations as the dependent variable.

4.2.1 Using the Spatial Lag Model

The spatial lag model is particularly effective in contexts where the variable of interest in one location is influenced by the same variable in neighboring locations. This study identifies a significant overlap in the spatial distribution of Housing Maintenance Code Violations and Rent Regulated Housing, suggesting that conditions in one area may affect neighboring areas. This could be due to factors like geographic proximity or proximity to common infrastructural resources to neighborhood effects, which often result in spatial autocorrelation. Incorporating a spatial lag term addresses this autocorrelation by accounting for the influence that the housing condition in one location might have on adjacent areas.

Traditional regression models typically assume that observations are independent. However, this assumption may not hold when the data exhibits spatial dependence, as observed in our study. Such spatial dependence can lead to biased and inefficient estimates, raising the risk of both type I and type II errors in statistical inference. To address this issue, our analysis incorporates a spatial lag model. This model enhances the accuracy and reliability of the estimates by including a spatial lag term, which corrects for the dependency among observations. The spatial lag model not only evaluates the direct effects of the independent variable—Rent Regulated Housing—on the dependent variable—Housing Maintenance Code Violations—but it also accounts for indirect effects(Anselin, 1988, 2002). These indirect effects arise from interactions among the dependent variable across neighboring spatial units. This adjustment makes the model more robust and suitable for empirical analysis, ensuring more reliable conclusions can be drawn from the data.

4.2.2 Spatial Regression Setup

Here is the model specification in the context of this study:

$$Y = \rho WY + X_1\beta_1 + X_2\beta_2 + X_3\beta_3 + \epsilon$$

where:

- Y is the dependent variable vector, which represents the number of house maintenance code violations per 1000 Households
- ρ (rho) is the spatial auto-regressive coefficient, which represents the degree to which the neighboring census tract's attributes influence the dependent variable of the census tract.
- W is the spatial weights matrix that defines the relationship between observations, as specified in Section 3.4.
- X_1 is the matrix of Rent Regulated Housings per 1000 Households.
- X_2 is the matrix of Number of Below 30% AMI Households per 1000 Households.
- X_3 is the matrix of Median Household Gross Rent.
- β_i are the vectors of coefficients associated with the independent variables.

- ϵ is the vector of error terms, assumed to be normally distributed.

The analysis of the link between rent regulation and housing maintenance issues progresses through a series of regression models, each building upon the previous one. The structured approach unfolds as follows:

1. **Initial Analysis with Ordinary Least Squares (OLS):** The study begins with an OLS regression model to establish baseline findings. This step involves validating basic statistical assumptions and ensuring the robustness of results using Heteroskedasticity and Auto-correlation Consistent (HAC) methods.

2. **Incorporation of Spatial Diagnostics:** After the initial OLS analysis, the study conducts spatial diagnostics to check for spatial dependence in the error terms. Tools such as Moran's I Test are employed to detect spatial auto-correlation and to elucidate the spatial relationships among data points, determining the necessity for a more sophisticated spatial model.

3. **Advanced Modeling with Spatial Lag Model:** If spatial dependence is confirmed, the analysis transitions to a spatial lag model that directly incorporates these dependencies into the regression framework. This model is also executed with HAC standard errors to maintain robustness against potential heteroskedasticity and auto-correlation in the spatial context.

Each stage of the analysis methodically integrates increasingly complex spatial elements, culminating in a comprehensive understanding of how rent regulations might influence housing maintenance code violations.

4.2.3 Non-Spatial OLS with HAC Standard Error

OLS regression results, as presented in Table 2, initially indicated that all three independent variables — rent-regulated housing, gross household rent, and the number of extremely low-income households—had predictive power for the dependent variable, Housing Maintenance Code Violations. These findings, reflecting an R-squared of 0.3624, suggested that approximately 36.24% of the variation in Housing Maintenance Code Violations per 1,000 households could be explained by these factors. Upon incorporating White's heteroskedasticity-consistent (HAC) robustness checks in Table 3, the predictive power of Median Household Rent was notably diminished. These preliminary results support the hypothesis that rent regulation and poverty levels are closely linked to issues of housing quality.

Table 2: OLS Regression Results for Housing Maintenance Code Violations

Variable	Coefficient	Std. Error	t-Statistic
CONSTANT	-109.33729	7.48702	-14.60358
Rent Regulated Units	3.75548***	0.17046	22.03086
Households Below 30 AMI	0.40767***	0.01630	25.00853
Median Gross Household Rent	-0.00000	0.00000	-1.68478
Number of Observations: 2226	*****:** P <0.01		
Adjusted R-squared: 0.3615			

Table 3: OLS with HAC Standard Error Results for Housing Maintenance Code Violations

Variable	Coefficient	Std. Error	t-Statistic
CONSTANT	-109.33729	11.20374	-9.75900
Rent Regulated Units	3.75548***	0.35093	10.70155
Households Below 30 AMI	0.40767***	0.02944	13.84950
Median Gross Household Rent	0.00000	0.00000	-3.64049
Number of Observations: 2226	*****:** P <0.01		
Adjusted R-squared: 0.3615			

4.2.4 OLS Model with Spatial Diagnostics

The spatial diagnostic analysis of the Ordinary Least Squares (OLS) model, focusing on housing maintenance code violation in New York City census tracts, identified spatial dependencies not evident in the initial non-spatial models. Specifically, Moran's I (error) test showed significant spatial autocorrelation in the erroes (value = 33.584, p = 0.0000), indicating variance due to spatial dependency not captured by the OLS models. This finding was supported by Lagrange Multiplier tests for both lag and error. The Lagrange Multiplier (lag) test (value = 1089.106, p = 0.0000) and the Robust LM (lag) test (value = 73.155, p = 0.0000) indicated significant spatial lag effects. Similarly, the Lagrange Multiplier (error) test (value = 1115.426, p = 0.0000) and the Robust LM (error) test (value = 99.475, p = 0.0000) demonstrated spatial autocorrelation in error terms. These results point to the need to explore spatial spillover effects of rent regulation on housing maintenance code violations, making the use of the Spatial Lag Model a logical next step.

4.2.5 Spatial Lag Model

With Spatial Diagnostics confirming spatial dependency among the variables tested, we employed a Spatial Lag Model to examine the influence of adjacent census tracts' demographics and rent regulation status on violations in each census tract. This model includes HAC adjustments for additional robustness checks.

In the Spatial Two Stage Least Squares (2SLS) model, which included a second-order spatial lag for the analysis of housing maintenance code violations across New York City census tracts, we uncovered significant spatial spillover effects. The model's findings, as detailed in Table 4, underscored the impact of neighboring tracts with the inclusion of spatially lagged housing maintenance code violations—denoted as **W_Violation**. This implies that the code violations in any given area are considerably influenced by the characteristics of adjacent areas.

Furthermore, the Anselin Kelejian (AK) Test yielded a value of 0.001 with a p-value of 0.9722, suggesting no significant residual spatial autocorrelation within the model after accounting for the spatial lag and other covariates. This result indicates that the Spatial Lag Model has effectively captured the spatial dependencies present in the housing code violations data for New York City's census tracts.

Table 4: Spatial Lag Model Result Summary

Variable	2017	2018	2019	2020	2021
CONSTANT	-61.143***	-59.526***	-45.046***	-32.610***	-45.680***
	(9.017)	(8.716)	(7.034)	(5.427)	(8.777)
Rent Regulated Units	2.632***	2.76758***	2.371***	1.90135***	2.561***
	(0.323)	(0.301)	(0.253)	(0.187)	(0.374)
Households Below 30 AMI	0.168***	0.16975***	0.133***	0.09850***	0.148***
	(0.027)	(0.028)	(0.024)	(0.020)	(0.035)
W_Violation	0.569***	0.616***	0.596***	0.721***	0.686***
	(0.053)	(0.049)	(0.052)	(0.042)	(0.061)

*p<0.01

4.2.6 Spillover Effects

In the investigation of housing maintenance code violations using Spatial Two Stage Least Squares (2SLS) analysis with a second-order spatial lag, the findings (Table 5) validate the hypothesized association between the prevalence of rent-regulated housing and the occurrence of maintenance code violations. The analysis elucidates that not only is there a direct relationship, but the spatial spillover effect—where attributes of neighboring census tracts significantly influence local conditions—is particularly pronounced(Anselin et al., 2000). This spillover effect surpasses the impact of local attributes alone, highlighting a pattern of interconnectedness in urban housing issues. This evidence corroborates the hypothesis that maintenance code violations are intertwined with the presence of rent-regulated housing and that their association extends beyond local boundaries to affect broader urban areas.

Table 5: LeSage-Pace: Percentage of Effect on Housing Maintenance Code Violation by Rent Regulations

Year	Within Census Tract(%)	From Neighbor Census Tracts (%)
2017	43.01	56.99
2018	38.31	61.69
2019	40.36	59.64
2020	27.83	72.17
2021	31.35	68.65

4.3 Before and After the Rent Law of 2019

The 2019 revamp of New York's rent stabilization laws represents a significant shift toward increased tenant protections, curbing the ability of landlords to raise rents and deregulate units. These reforms entail crucial changes, such as the abolition of vacancy decontrol, which prevented the automatic exit of apartments from the stabilization system due to reaching high vacancy rents. The vacancy bonus, which previously allowed a rent increase of up to 20% upon tenant turnover, was also eliminated. Additionally, rent increases are now constrained by preferential rents rather than the legal maximum, with the Rent Guidelines Board setting strict caps, thus shielding tenants from abrupt and excessive rent hikes. The legislation further imposes new limits on the increments landlords can charge tenants for both building-wide and individual apartment improvements, which were often a gateway to rent inflation following renovations (Housing Stability & Tenant Protection Act of 2019, State of New York).

Against this backdrop of strengthened regulations, this study tests the hypothesis that the enactment of more restrictive rent laws might lead to an increase in the prevalence of maintenance code violations. The concern is that, while the laws aim to protect tenants, they could inadvertently incentivize increased reporting of violations or result in diminished maintenance investments by landlords. By adopting the analytical framework of Card and Krueger (Card and Krueger, 1993), this study extends its methodology to evaluate the effects of stringent rent laws on housing quality. Utilizing a difference-in-differences approach, the analysis examines the temporal shifts in violation reports between the rent-regulated lots (the treatment group) and non-regulated lots (the control group), thereby establishing some causal impacts of the new rent regulations.

Treatment Groups: Lot (Building) characterized by having Rent Regulated Housing.

These areas are subjected to the new rent regulations effective from June 15, 2019, thereby serving as the treatment group.

Control Groups: Lot (Building) without Rent Regulated Housing serves as the control group. These areas provide a baseline for comparison as they are not affected by the new legislative measures.

4.3.1 Data and Limitation

Housing maintenance code violation data, vital for the treatment and control groups in this study, are compiled with a clear demarcation between the pre- and post-treatment periods. The cutoff between these periods aligns with the enactment date of the new rent laws—June 14, 2019. Therefore, data leading up to this date will be classified as pre-treatment, while data from June 15, 2019, onwards will be considered post-treatment.

It is important to note, however, that the dataset has inherent limitations. The records of housing code violations do not encompass the entirety of housing quality issues across New York City but represent only the instances that have been formally reported and cited by city housing inspectors. This means that the data may not fully capture unreported violations or underlying issues that have not yet been observed or processed by inspection authorities. Therefore, while the data serve as an important indicator of housing quality, they should be understood as a subset of the actual housing conditions experienced by residents.

4.3.2 Diff-in-Diff Setup

The difference-in-differences analysis is conducted by estimating the following regression model:

$$Y_{it} = \beta_0 + \beta_1 \text{Post}_t + \beta_2 \text{Treatment}_i + \beta_3 (\text{Post}_t \times \text{Treatment}_i) + \epsilon_{it}$$

Where:

- Y_{it} represents the number of violations in Lot i at time t.
- Post_t is a binary variable that indicates the period after the enactment of the Rent Law of 2019.
- Treatment_i is a binary variable that indicates whether the Lot is under rent regulation.
- β_3 (the coefficient of the interaction term) captures the differential effect of the Rent Law on the treated regions relative to the control regions.

4.3.3 Diff-Diff Results

The OLS regression analysis (Table 6) reveals that the model explains about 6.1% of the variation in violations of the housing maintenance code, suggesting that future studies should include additional variables for better specificity and model fit. Statistically significant results indicate that rent-regulated buildings experience a substantial increase in violations compared to non-regulated buildings, with an average increase of 35.34 violations per unit. Furthermore, the implementation of the 2019 housing laws appears to exacerbate these issues, as evidenced by a statistically significant interaction term, which shows an additional increase of approximately 5.99 violations in rent-regulated units post-legislation. This finding suggests that while the intent behind the new laws was likely to protect tenants, they may have inadvertently led to an increase in reported violations, possibly due to enhanced enforcement by housing agencies, increased tenant reporting, or reduced landlord investments in property maintenance. The data points available for analysis show that rent-regulated housing experienced a higher level of violations, which became more severe after the more restrictive rent law came into effect. This supports the hypothesis that stringent rent law is linked to the increase in the prevalence of maintenance code violations, highlighting the unintended consequences of these regulatory changes on housing quality.

Table 6: OLS Regression Results for Housing Code Violations

	Coefficient	**Std. Error**	**t-Statistics**	**Probability**
Intercept	10.4517	0.209	49.912	0.000
Rent Regulated	35.3441	1.266	27.923	0.000
After19	2.5363	0.234	10.843	0.000
After19:Rent Regulated	5.9886	0.652	9.187	0.000
Observations	137634			
R-squared	0.061			
Adj. R-squared	0.061			
F-statistic	375.4			
Prob (F-statistic)	4.81e-197			
Log-Likelihood	-791740			
AIC	1583000			
BIC	1584000			

5 Discussion

To explore the hypothesis that maintenance code violations and rent-regulated housing are clustered and overlap, this study employed spatial clustering methods using Global and Local Moran's I statistics. The analysis confirmed significant clustering of both housing maintenance code violations and rent-regulated housing across New York City, indicating that these phenomena are not randomly distributed but are geographically concentrated. Detailed local analysis revealed stark differences in housing quality between higher-income and lower-income neighborhoods, with areas such as Manhattan's Upper East Side showing fewer violations compared to economically disadvantaged areas like Harlem. This pattern was consistent across other boroughs, suggesting that socioeconomic status is a major determinant of housing quality. The study also found that neighborhoods with higher concentrations of rent-regulated units tend to face greater housing quality issues, which underlines the impact of rent regulation on housing conditions.

The spatial regression analysis across New York City's census tracts has consistently identified rent regulation as a robust and significant predictor for housing maintenance code violations. This finding holds true across various models with or without spatial components, including Ordinary Least Squares (OLS), Spatial Lag Models with robustness check, illustrating the influence of rent-regulated units on housing maintenance code violations. The presence of spatial dependence and spillover effects, particularly in models accounting for spatial lags, highlights that neighboring tracts' rent-regulated housing and demographics can influence housing maintenance code violations in a given tract.

To test the hypothesis that stringent rent laws increase the prevalence of maintenance code violations, this study utilized a difference-in-differences approach, contrasting changes between census tracts affected by the 2019 rent stabilization reforms (treatment group) and those not affected (control group). The reforms, which significantly curtailed the ability of landlords to increase rents and deregulate units, provided a natural experiment to observe the impact of such policies on housing quality. Findings indicate that the implementation of these laws correlated with an increase in reported maintenance code violations in rent-regulated units, suggesting that while the laws aim to protect tenants, they might inadvertently lead to diminished property upkeep or increased reporting of violations. This supports the hypothesis that more restrictive rent laws can lead to a higher incidence of reported maintenance issues as the unintended consequences of these rent regulations on housing quality.

6 Limitation

Theoretically, this research aimed to link housing code violations as a force disproportionately affecting lower-income populations, who are most impacted by gentrification. It posited that landlords restricted by rent regulations might be incentivized to allow property quality to deteriorate. This could serve a dual purpose: achieving higher returns upon deregulation and driving out low-income tenants. However, the scope of the violation data does not allow for an examination of landlords' intentions nor does it fully represent the actual state of housing quality. This limitation makes it inconclusive to firmly establish a causal connection between rent regulations, property neglect by landlords, and the processes of gentrification, pointing to a significant gap that future research could address to better understand these dynamics.

The present study, which explores housing code violations as a proxy for housing quality to assess the impact of rent regulation on gentrification, encompasses several limitations that may affect its internal validity. Firstly, the reliance on tenant reports rather than proactive inspections may not fully capture the extent of housing quality issues, as not all complaints result in officially recognized code violations. The determination of these violations relies heavily on inspectors' judgments, potentially introducing biases that could skew outcomes. Additionally, the cyclical nature of housing code violations, with seasonal fluctuations in types and frequencies, complicates the analysis of housing issues.

The research employs census tract data to analyze housing code violations, which may not capture critical finer-scale variations necessary for a thorough understanding of housing deterioration. This level of granularity, although beneficial for identifying broad patterns, might mask localized discrepancies that are important in analyzing the dynamics of housing quality. Additionally, the potential under-specification of the spatial regression models used in the study could lead to omitted variable bias, as not all relevant variables influencing housing code violations are accounted for, potentially skewing results. The observed non-normality of residuals in several models indicates violations of classical linear regression assumptions, which could undermine the validity of statistical inferences drawn from the data.

Moreover, while rent regulation is identified as a significant predictor of housing code violations, it is clear that other unaccounted factors also play crucial roles. The absence of these variables from the models could distort the true impact of rent regulation on housing quality. On the demographic and economic front, the data available lacks the finer granularity that might provide a deeper insight into how neighborhood-specific dynamics affect housing conditions. Future studies could benefit from narrowing the scope of analysis to the neighborhood or even tax lot level, leveraging more detailed data to better understand how rent regulation impacts housing quality and potentially facilitates the displacement of lower-income populations. This more granular approach could offer a clearer picture of the local effects of rent regulations and their implications for urban housing policy.

While the analyses conducted in this study elucidate a pronounced spatial correlation between rent regulation and housing deterioration, it is imperative to emphasize that these findings do not establish causation conclusively. The observed correlations provide an initial understanding but fall short of substantiating that rent regulation directly precipitates housing deterioration. This recognition highlights a substantial gap, accentuating the necessity for future research to deploy methodologies that can yield more robust causal inferences. Subsequent studies should endeavor to delineate the direct impacts of rent regulation on housing quality, transcending correlation to unearth the underlying causative mechanisms. In response to the limitations identified in the current study and to enhance causal inference, the development of an agent-based model (ABM) could prove highly advantageous. This model would simulate the intricate interactions between household mobility and urban housing conditions, focusing specifically on the cycles of decay and reinvestment, along with the dynamics of violation reporting behaviors. The ABM would incorporate agents representing both households and census tracts, characterized by attributes such as income levels, housing quality, rent stabilization status, and migration patterns. By modeling the decision-making processes of households in reaction to shifts in housing conditions and policy landscapes—including their propensity to report violations and their mobility within and across neighborhoods—this approach could furnish deeper insights into the causal mechanisms linking rent regulation to housing quality. Such an advanced analytical framework would not only address the extant study's limitations but also provide more definitive insights into how rent regulation influences housing conditions.

7 Conclusion

The intricate balance between affordability and housing quality in urban landscapes like New York City remains a pressing issue. Rent regulation policies, while intended to safeguard tenants from displacement and maintain affordability, have been shown to have unintended consequences that affect both social and physical aspects of neighborhoods. This paper showcased the empirical association between rent regulation policies and housing deterioration through spatial analyses. These consequences extend beyond the mere anticipation of capital returns and can deeply influence the living experiences of communities ensconced within these urban contours.

This research has employed a forward specification approach, with each method building upon the previous to test three increasingly specific hypotheses. Initially, spatial clustering algorithms were employed to identify concentration overlaps between rent regulation and violation variables. Then, a series of spatial regression models were utilized to examine the spatial dependencies among these variables. Finally, a non-spatial difference-in-differences analysis was conducted to provide some insights for causal inferences. This analysis treated rent regulation as the intervention variable, with the enactment of the 2019 rent law serving as the intervention. By systematically progressing through these methods, this paper has found that the stricter rent regulation policies on rent-regulated units are associated with an increase in housing maintenance code violations, thus providing valuable insights into the efficacy of rent regulation policies in New York City.

Navigating the complexities of urban change, the view of cities as places of both economic opportunity and social flux rings true (Lauermann, 2021, 2022). The ebb and flow of policies and investments shape cities and influence the balance of housing affordability with quality. The cycle of neglect and redevelopment in rent-regulated properties reveals a pattern of disinvestment and gentrification, which worsens urban inequality (Dangschat, 2023; Fields, 2015; Lees et al., 2013) Wealth and poverty often stand side by side at the expense of marginalized communities. While some advocate for government policies that encourage redevelopment and the conversion of rent-regulated units to stimulate economic growth (Fernandez and Aalbers, 2016), such approaches frequently prioritize economic objectives at the expense of preserving community cohesion and affordable housing, risking the erosion of community identity and the exacerbation of housing disparities.

Therefore, to tackle these challenges, policymakers must take a thoughtful approach by scrutinizing the unintended consequences of rent regulation policies and considering potential adjustments to mitigate negative impacts. Building on this research, future research can find more evidence on the potential causality between rent regulation policies and housing quality deterioration and the potential association between housing regulation policies and gentrification, which is not concluded by this research due to limited resources. Eventually, policymakers should work towards solutions that promote equitable access to quality, affordable housing for all residents and build inclusive urban communities.

Data and Code Availability Statement

The paper uses data obtained from NYC OpenData and the U.S. Census Bureau. Cleaned data, including codes for preprocessing, cleaning, structuring, and analyses are accessible from GitHub repo here for replication purposes.

References

Albon, R. P., & Stafford, D. C. (1990). Rent Control and Housing Maintenance [Publisher: SAGE Publications Ltd]. *Urban Studies*, *27*(2), 233–240. https://doi.org/10.1080/00420989020080191

Anselin, L. (1988). *Spatial Econometrics: Methods and Models*. Retrieved April 29, 2024, from https://link.springer.com/book/10.1007/978-94-015-7799-1

Anselin, L. (1996). The Moran scatterplot as an ESDA tool to assess local instability in spatial association [Num Pages: 16]. In *Spatial Analytical Perspectives on GIS*. Routledge.

Anselin, L. (2002). Under the hood Issues in the specification and interpretation of spatial regression models [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1574-0862.2002.tb00120.x]. *Agricultural Economics*, *27*(3), 247–267. https://doi.org/10.1111/j.1574-0862.2002.tb00120.x

Anselin, L., Varga, A., & Acs, Z. (2000). Geographical Spillovers and University Research: A Spatial EconometricPerspective [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/0017-4815.00142]. *Growth and Change*, *31*(4), 501–515. https://doi.org/10.1111/0017-4815.00142

Arnott, R. (1995). Time for Revisionism on Rent Control? [Publisher: American Economic Association]. *The Journal of Economic Perspectives*, *9*(1), 99–120. Retrieved November 9, 2023, from https://www.jstor.org/stable/2138358

Arnott, R., & Stiglitz, J. (1981). Aggregate Land Rents and Aggregate Transport Costs [Publisher: Royal Economic Society]. *Economic Journal*, *91*(362), 331–47. Retrieved April 1, 2024, from https://econpapers.repec.org/article/ecjeconjl/v_3a91_3ay_3a1981_3ai_3a362_3ap_3a331-47.htm

Asquith, B. J. (2019). Housing Supply Dynamics under Rent Control: What Can Evictions Tell Us? *AEA Papers and Proceedings*, *109*, 393–396. https://doi.org/10.1257/pandp.20191025

Atkinson, R., & Wulff, M. (2009). Gentrification and displacement: A review of approaches and findings in the literature (positioning paper). Retrieved April 1, 2024, from https://apo.org.au/node/15334

Card, D., & Krueger, A. B. (1993, October). Minimum Wages and Employment: A Case Study of the Fast Food Industry in New Jersey and Pennsylvania. https://doi.org/10.3386/w4509

Dangschat, J. S. (2023). Gentrification as a self-producing and self-reenforcing process on the macro, meso and micro level. In A. Barth, F. Leßke, R. Atakan, M. Schmidt, & Y. Scheit (Eds.), *Multivariate scaling methods and the reconstruction of social* *spaces* (1st ed., pp. 131–148). Verlag Barbara Budrich. https://doi.org/10.2307/jj.7330043.10

Davidson, M., & Lees, L. (2010). New-build gentrification: Its histories, trajectories, and critical geographies: Critical Geographies of New-Build Gentrification. *Population, Space and Place*, *16*(5), 395–411. https://doi.org/10.1002/psp.584

Desmond, M., & Shollenberger, T. (2015). Forced Displacement From Rental Housing: Prevalence and Neighborhood Consequences. *Demography*, *52*(5), 1751–1772. https://doi.org/10.1007/s13524-015-0419-9

Diamond, R., McQuade, T., & Qian, F. (2019). The Effects of Rent Control Expansion on Tenants, Landlords, and Inequality: Evidence from San Francisco. *American Economic Review*, *109*(9), 3365–3394. https://doi.org/10.1257/aer.20181289

Easton, S., Lees, L., Hubbard, P., & Tate, N. (2020). Measuring and mapping displacement: The problem of quantification in the battle against gentrification [Publisher: SAGE Publications Ltd]. *Urban Studies*, *57*(2), 286–306. https://doi.org/10.1177/0042098019851953

Epstein, R. (1988). Rent Control and the Theory of Efficient Regulation. *Brooklyn Law Review*, *54*, 741. https://chicagounbound.uchicago.edu/journal_articles/1327

Fainstein, S. S., & Campbell, S. (Eds.). (2016). *Readings in planning theory* (Fourth edition). Wiley/Blackwell.

Fairbanks, R. P. (2009). *How it works: Recovering citizens in post-welfare Philadelphia* [OCLC: 526106701]. University of Chicago Press. Retrieved April 1, 2024, from https://catalog.lib.uchicago.edu/vufind/Record/11282742

Fernandez, R., & Aalbers, M. B. (2016). Financialization and housing: Between globalization and Varieties of Capitalism [Publisher: SAGE Publications Ltd]. *Competition & Change*, *20*(2), 71–88. https://doi.org/10.1177/1024529415623916

Fields, D. (2015). Contesting the Financialization of Urban Space: Community Organizations and the Struggle to Preserve Affordable Rental Housing in New York City. *Journal of Urban Affairs*, *37*(2), 144–165. https://doi.org/10.1111/juaf.12098

Glaeser, E. L., & Gyourko, J. (2005). Urban Decline and Durable Housing [Publisher: The University of Chicago Press]. *Journal of Political Economy*, *113*(2), 345–375. https://doi.org/10.1086/427465

Glaeser, E. L., & Luttmer, E. F. P. (2003). The Misallocation of Housing Under Rent Control. *American Economic Review*, *93*(4), 1027–1046. https://doi.org/10.1257/000282803769206188

Gyourko, J., & Linneman, P. (1990). Rent controls and rental housing quality: A note on the effects of New York City's old controls. *Journal of Urban Economics*, *27*(3), 398–409. https://doi.org/10.1016/0094-1190(90)90009-C

Harcourt, B. E. (2001). *Illusion of order: The false promise of broken windows policing*. Harvard University Press. Retrieved April 1, 2024, from https://catalog.lib.uchicago.edu/vufind/Record/4478537

Harvey, D. (2003). *PARIS, CAPITAL OF MODERNITY* [OCLC: 1199127296]. ROUTLEDGE.

Holm, A., & Schulz, G. (2018). GentriMap: A Model for Measuring Gentrification and Displacement. In I. Helbrecht (Ed.), *Gentrification and Resistance: Researching Displacement Processes and Adaption Strategies* (pp. 251–277). Springer Fachmedien. https://doi.org/10.1007/978-3-658-20388-7_10

Kearl, J. R. (1979). Inflation, Mortgage, and Housing [Publisher: University of Chicago Press]. *Journal of Political Economy*, *87*(5), 1115–1138. Retrieved April 1, 2024, from https://www.jstor.org/stable/1833085

Klinenberg, E. (2003, July). *Heat Wave: A Social Autopsy of Disaster in Chicago* [Google-Books-ID: KpRY0HNza4sC]. University of Chicago Press.

Kutty, N. K. (1996). The impact of rent control on housing maintenance: A dynamic analysis incorporating European and North American rent regulations [Publisher: Taylor & Francis Group]. *Housing Studies*. https://doi.org/10.1080/02673039608720846

Lauermann, J. (2021). Luxury housing and gentrification in New York City, 2010-2019. *Urban Geography*, 1–19. https://doi.org/10.1080/02723638.2021.1956112

Lauermann, J. (2022). Vertical Gentrification: A 3D Analysis of Luxury Housing Development in New York City [Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/24694452.2021.202
Annals of the American Association of Geographers, *112*(3), 772–780. https://doi.org/10.1080/24694452.2021.2022451

Lees, L., Slater, T., & Wyly, E. (2013, October). *Gentrification* (0th ed.). Routledge. https://doi.org/10.4324/9780203940877

Liu, C., O'Sullivan, D., & Perry, G. L. W. (2018). The rent gap revisited: Gentrification in point Chevalier, Auckland [Publisher: Routledge _eprint: https://doi.org/10.1080/02723638.2018.144688
Urban Geography, *39*(9), 1300–1325. https://doi.org/10.1080/02723638.2018.1446883

Logan, J. R., Molotch, H. L., & Molotch, H. L. (1987). *Urban fortunes: The political economy of place* (1. pr.). Univ. of California Press.

Madden, D. J., & Marcuse, P. (2016). *In defense of housing: The politics of crisis* [OCLC: 936360438]. Verso. Retrieved April 1, 2024, from https://catalog.lib.uchicago.edu/vufind/Record/11424812

Maloutas, T. (2012). Contextual Diversity in Gentrification Research. *Critical Sociology*, *38*(1), 33–48. https://doi.org/10.1177/0896920510380950

Moon, C.-G., & Stotsky, J. G. (1993). The Effect of Rent Control on Housing Quality Change: A Longitudinal Analysis [Publisher: University of Chicago Press]. *Journal of Political Economy*, *101*(6), 1114–1148. Retrieved November 8, 2023, from https://www.jstor.org/stable/2138574

Moorhouse, J. C. (1972). Optimal Housing Maintenance under Rent Control [Publisher: Southern Economic Association]. *Southern Economic Journal*, *39*(1), 93–106. https://doi.org/10.2307/1056228

Novak, W. J. (1996). *The people's welfare: Law and regulation in nineteenth-century America* [OCLC: 45727904]. University of North Carolina Press. Retrieved April 1, 2024, from https://catalog.lib.uchicago.edu/vufind/Record/11109666

Olsen, E. O. (1972). An Econometric Analysis of Rent Control [Publisher: University of Chicago Press]. *Journal of Political Economy*, *80*(6), 1081–1100. Retrieved November 8, 2023, from https://www.jstor.org/stable/1830211

Olsen, E. O. (1988). What Do Economists Know About the Effect of Rent Control on Housing Maintenance?: Journal of Real Estate Finance & Economics [Publisher: Springer Nature]. *Journal of Real Estate Finance & Economics*, *1*(3), 295–307. https://doi.org/10.1007/BF00658922

Patch, J., & Brenner, N. (2007). Gentrification [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/97814 In *The Blackwell Encyclopedia of Sociology*. John Wiley & Sons, Ltd. https://doi.org/10.1002/9781405165518.wbeosg035

Pinkney, D. H. (1978). Paris La Ville, 1852-1870: L'Urbanisme parisien a l'heure d'Haussmann; Des provinciaux aux parisiens; La Vocation ou les vocations parisiennes. By Jeanne Gaillard. (Paris: Editions Honore Champion, 1977. 686 pp.) *Journal of Social History*, *12*(2), 331–333. https://doi.org/10.1353/jsh/12.2.331

Rosen, E. (2014). Rigging the Rules of the Game: How Landlords Geographically Sort Low–Income Renters [Publisher: SAGE Publications]. *City & Community*, *13*(4), 310–340. https://doi.org/10.1111/cico.12087

Rosen, E., Garboden, P. M. E., & Cossyleon, J. E. (2021). Racial Discrimination in Housing: How Landlords Use Algorithms and Home Visits to Screen Tenants [Publisher: SAGE Publications Inc]. *American Sociological Review*, *86*(5), 787–822. https://doi.org/10.1177/00031224211029618

Rydell, C. P., Barnett, C. L., Hillestad, C. E., Murray, M., Neels, K., & Sims, R. H. (1981, January). *The Impact of Rent Control on the Los Angeles Housing Market* (tech. rep.). RAND Corporation. Retrieved March 25, 2024, from https://www.rand.org/pubs/notes/N1747.html

Sampson, R. J., & Raudenbush, S. W. (2004). Seeing Disorder: Neighborhood Stigma and the Social Construction of "Broken Windows" [Publisher: SAGE Publications

Inc]. *Social Psychology Quarterly*, *67*(4), 319–342. https://doi.org/10.1177/019027250406700401

Satter, B. (2009). *Family properties: Race, real estate, and the exploitation of Black urban America* (1st ed). Metropolitan Books. Retrieved April 1, 2024, from https://catalog.lib.uchicago.edu/vufind/Record/7630114

Sims, J. R. (2021). Measuring the Effect of Gentrification on Displacement: Multifamily Housing and Eviction in Wisconsin's Madison Urban Region [Publisher: Routledge _eprint: https://doi.org/10.1080/10511482.2021.1871931]. *Housing Policy Debate*, *31*(3-5), 736–761. https://doi.org/10.1080/10511482.2021.1871931

Slater, T. (2017). Planetary Rent Gaps: Planetary Rent Gaps. *Antipode*, *49*, 114–137. https://doi.org/10.1111/anti.12185

Slater, T. (2021). From displacements to rent control and housing justice [Publisher: Routledge _eprint: https://doi.org/10.1080/02723638.2021.1958473]. *Urban Geography*, *42*(5), 701–712. https://doi.org/10.1080/02723638.2021.1958473

Smith, N. (1979). Toward a Theory of Gentrification A Back to the City Movement by Capital, not People [Publisher: Routledge _eprint: https://doi.org/10.1080/01944367908977002]. *Journal of the American Planning Association*, *45*(4), 538–548. https://doi.org/10.1080/01944367908977002

Smith, N. (1987). Gentrification and the Rent Gap [Publisher: Routledge _eprint: https://doi.org/10.1111/j.1467
8306.1987.tb00171.x]. *Annals of the Association of American Geographers*, *77*(3), 462–465. https://doi.org/10.1111/j.1467-8306.1987.tb00171.x

Smith, N. (2005). *The new urban frontier gentrification and the revanchist city* [OCLC: 1229290024]. Routledge.

Topel, R., & Rosen, S. (1988). Housing Investment in the United States [Publisher: University of Chicago Press]. *Journal of Political Economy*, *96*(4), 718–740. Retrieved April 1, 2024, from https://www.jstor.org/stable/1830471

Valverde, M. (2011). Seeing Like a City: The Dialectic of Modern and Premodern Ways of Seeing in Urban Governance [Publisher: [Wiley, Law and Society Association]]. *Law & Society Review*, *45*(2), 277–312. Retrieved April 1, 2024, from https://www.jstor.org/stable/23012043

Wyly, E. K., & Hammel, D. J. (1999). Islands of decay in seas of renewal: Housing policy and the resurgence of gentrification [Publisher: Routledge _eprint: https://doi.org/10.1080/10511482.1999.95
Housing Policy Debate, *10*(4), 711–771. https://doi.org/10.1080/10511482.1999.9521348

Ye, T., Johnson, R., Fu, S., Copeny, J., Donnelly, B., Freeman, A., Lima, M., Walsh, J., & Ghani, R. (2019). Using machine learning to help vulnerable tenants in New

York city. *Proceedings of the 2nd ACM SIGCAS Conference on Computing and Sustainable Societies*, 248–258. https://doi.org/10.1145/3314344.3332484