Subsidizing Gentrification?: Neighborhood Change and the Expansion of the 421a Geographic Exclusion Area

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Abstract

In 2008, the Geographic Exclusion Area (GEA) of New York City's 421a tax exemption program was expanded from central Manhattan to include large swaths of all five boroughs. With a billion-dollar annual price tag, 421a is one of the largest municipal tax breaks to developers in the nation; however, at the time of the expansion, only within the GEA were developers required to provide affordable housing to receive these benefits. Catalyzed by mounting public opposition to 421a, the GEA expansion marked city and state leaders' commitment to the program as an affordable housing policy capable of combating gentrification and growing inequality in New York City. Despite this show of confidence, the program's effects on these trends has not been comprehensively analyzed. In this paper, I deploy a mixed-methods analysis of 421a to understand its effectiveness as an affordable housing policy, using the 2008 GEA expansion as a spatial and temporal case study. Through this research, I conclude that 421a directly accelerates the emergence of income inequality and unaffordable housing in New York, thereby creating the very neighborhoods of inequity and exclusivity that it was designed to prevent. In this way, 421a can be categorized as one of, rather than distinct from, the many problematic programs in the neoliberal suite of affordable housing policy that drives American planning today.

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List of Abbreviations

421a Policy

421a: Section 421-a of the New York State Real Property Tax Law

AHNY: Affordable Housing New York Program (post-2016 version of 421a)

ANNY: Affordable Neighborhoods for New Yorkers Program (proposed update to 421a/AHNY)

GEA: Geographic Expansion Area

General Affordable Housing Terminology

AMI: Area median income (defined by HUD)

DU: Dwelling unit

GSF: Gross square footage

HDFC: Housing Development Fund Corporation

MSA: Metropolitan statistical area

SF: Total square footage

Government Agencies

DCP: New York City Department of City Planning

DHCR: New York State Division of Homes & Community Renewal

DOB: New York City Department of Buildings

DOF: New York City Department of Finance

HDC: New York City Housing Development Corporation

HFA: New York State Housing Finance Agency

HPD: New York City Department of Housing Preservation & Development

HUD: United States Department of Housing & Urban Development

Affordable Housing Programs

CDBG: Community Development Block Grant (HUD)

ELLA: New York City Extremely Low- and Low-Income Affordability program (HPD)

HTF: Federal Housing Trust Fund (HUD)

HWF: New York State Homes for Working Families program (DHCR)

MIH: New York City Mandatory Inclusionary Housing program (HPD/DCP)

MIHP: New York State Middle Income Housing Program (DHCR)

NCP: New York City/State Neighborhood Construction Program/New Construction Program (HPD/DHCR)

RAD: Rental Assistance Demonstration (HUD)

SHOP: New York State Supportive Housing Opportunity Program (SHOP)

SLIHC: New York State Low-Income Housing Tax Credit program (DHCR)

VIH: New York City Voluntary Inclusionary Housing program (HPD/DCP)

Data & Methodology

ACS: American Community Survey (administered by the United States Census Bureau)

CHAS: Comprehensive Housing Affordability Strategy (database maintained by HUD)

CT2000: Census tract, 2000 boundaries

CT2010: Census tract, 2010 boundaries

DiD: Difference-in-differences model

POLR: Proportional odds logit regression model

VIF: Variable inflation factor collinearity analysis

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Chapter 1: Introduction

1.1 Research Context

Section 421-a of the New York State Real Property Tax Law ("421a") is one of the defining public programs in New York City's real estate sector. Established in 1971 by the New York State Legislature, 421a offers a full property tax exemption to new multifamily residential developments, usually for a period of 15 to 25 years. Throughout its lifespan, 421a has been amended with various new qualification requirements.

Among the most significant amendments to 421a was the introduction and expansion of the Geographic Exclusion Area ("GEA"). Prior to the introduction of the GEA, developments were not subject to any residential affordability requirements to qualify for 421a benefits. In 1985, the program was amended to include the GEA, which originally consisted of Manhattan between 14th and 96th Streets. Within the GEA, developments had to make 20% of units affordable as certified by the NYC Department of Housing Preservation & Development ("HPD"). Outside the GEA, any residential development qualified for 421a as-of-right.

In 2006, with 421a up for renewal, state and city officials proposed expanding the GEA to new areas. Between 2006 and 2008, incremental expansions eventually grew the GEA to include all of Manhattan, much of west Brooklyn and Queens, and small parts of the south Bronx and north Staten Island. This amended version of 421a was adopted in late 2008 and remained in place through the end of 2015 when the 421a program, once again up for renewal, was phased out altogether and succeeded by the Affordable Housing New York program ("AHNY"). AHNY requires all buildings, regardless of location, to include affordable units to qualify, eliminating the need for the GEA. In all, the expanded GEA was in place for just over seven full years (2009-2015).

1.2 Research Purpose & Questions

The purpose of this study is to analyze neighborhood-level impacts of the 2009-2015 expansion of the GEA. Critics of 421a have long argued that the program inequitably conveys public funds to private investors and property owners without ensuring the provision of public benefits. The implementation and subsequent expansion of the GEA were among many efforts by public leaders to mitigate these concerns. However, the impact of this expansion on affected communities remains unclear. Many neighborhoods adopted into this expansion of the GEA, such as Williamsburg in Brooklyn and the Lower East Side in Manhattan, have been among the City's most infamous cases of gentrification and surging housing costs since the GEA was expanded. However, the degree and direction of the impact of the GEA expansion on these changes remains unclear.

My research implements a quasi-experimental difference-in-differences analysis of longitudinal data, supported by a qualitative policy analysis, to determine the relationship between the GEA expansion and temporal changes in seven neighborhood indicators[1]:

- **Neighborhood change score:** The degree of change of a neighborhood's social exclusivity relative to the previous year[2].
- **Entropy index:** A multigroup measure of racial segregation within a neighborhood[3].
- **Gini coefficient:** A measure of the degree of income inequality within a neighborhood.
- **80/20 ratio:** The ratio of the 80th income percentile within a neighborhood to the 20th percentile.
- **Geographic mobility:** The percentage of residents in a neighborhood who lived elsewhere the previous year.

1. For detailed explanations and formulas, see Methodology.
2. Proposed by Collins (2015).
3. Proposed by Theil and Finizza (1971); sometimes known as Theil's Entropy index.

- **Local renter affordability index:** The probability that a resident of a given neighborhood can find an affordable rental unit within the same neighborhood.
- **Citywide renter affordability index:** The probability that a resident of New York City can find an affordable rental unit within a certain neighborhood[4].

These indicators are intended to capture a cross-section of concerns related to equity, gentrification, and residential affordability. Through this analysis, I address three primary research questions:

1. How did key social and spatial conditions change across neighborhoods in New York City from 2000-2019?
2. To what extent did these changes differ in degree and/or direction within the GEA compared with the rest of the city?
3. For neighborhoods not included within the original GEA, to what extent did the expansion of the GEA alter the degree and direction of these neighborhood changes between 2009 and 2016?

1.3 Research Significance

Although 421a has been replaced by AHNY, the policies are different largely in name only, with the key exception of the new universal affordability requirement under AHNY. In most other ways, AHNY replicates the rules and motivations of 421a - as well as many of its perceived successes and shortcomings. With the 421a/AHNY program set to expire in 2022, City and State leaders are engaged in ongoing discussions around whether and how to renew or replace the program. In January 2022, Governor Kathy Hochul proposed an alternative program titled the Affordable Neighborhoods for New Yorkers program ("ANNY") that would replace 421a/AHNY. ANNY would establish a new section of the state's tax code (485-w) as

4. Both affordability indices are based on the Homeownership Affordability for Renters model proposed by Goodman, Li, and Zhu (2018).

well as renaming the program, thereby suggesting an overhaul of the decades-old structure of 421a (Hochul 2022). Gov. Hochul's proposal would indeed restructure the incentive options for developers to increase the affordability requirements from a 130% AMI cap to just 90% AMI. ANNY would also increase the required affordability term - projects with more than 30 residential units would be required to maintain affordability in perpetuity, while those under 30 units would have a required affordability term of 35 years with rent stabilization requirements imposed afterwards. Both figures were previously tied to the length of the 421a exemption, which ranged from 10 to 35 years. Despite these improvements, the structure of ANNY is highly similar to 421a/AHNY. Although real estate leaders have lauded Gov. Hochul's proposal, housing advocates have criticized these changes as "window dressing" that fails to consider more comprehensive policy alternatives that directly target affordable housing development (Lewis 2022). Despite marginal changes from 421a to AHNY to ANNY, experts suggest, these policies are structurally more synonymous than they are distinct.

As this debate between political leaders and housing advocates continues, it is imperative that new research analyze the recent effects of the policy approach utilized in 421a/AHNY/ANNY. Housing policies that mitigate inequity, unaffordability, gentrification, and segregation are imperative. While the 421a policy family is intended to do this, much attention has been drawn to the ways in which the program has at best failed to meet its goals and at worst exacerbated these trends. Given the massive financial cost of maintaining the program under its current structure, it is critical to ensure that these resources are mitigating these issues rather than worsening them.

Researchers and policymakers have struggled to quantify the impact of 421a as a tool for improving equity and affordability because of the longevity of the program and the dramatic changes in the fabric of New York City over the same period. However, the recent, yet brief, expansion of the GEA provides a unique opportunity to isolate the neighborhood-level impacts of 421a's affordability requirements - the same requirements which form the core of the amended ANNY policy. With this expansion as a spatial proxy for tracking the local

impacts of this policy approach, my research will highlight recent relationships between the 421a program and key neighborhood indicators. These findings may inform the forthcoming conversation around renewing or replacing the program and provide a broader reference point for tracking recent socio-spatial changes and inequities in New York City.

Chapter 2: Literature Review

2.1 History and Impacts of 421a

New York's 421a tax exemption is one of the most prolific public-private development partnerships in the city. Established in 1971, 421a offers property tax exemptions, usually for a period of 15 to 25 years, to new multifamily residential developments (421a Benefits Statute 2016). Initially, the goals of 421a did not include affordable housing creation. The program was created in the context of the development crisis in NYC in the 1970s, during which time the city lost 10% of its population as residents fled to the suburbs and residential development across the five boroughs ground largely to a halt (Cohen 2009). To broadly stimulate the development of multifamily housing, 421a was offered to nearly any developer interested in pursuing residential projects anywhere in the city and at any price with the stated intention of facilitating the creation of new high-quality residential units (Konopko 1987). In its early days, 421a offered a full tax exemption during construction and for the first ten years of operation. Only one affordability component was included in the original bill: units receiving 421a benefits were subject to the City's new rent stabilization regulations for the duration of the tax exemption. The New York State Legislature passed the bill, although its benefits were (and continue to be) administered by HPD. Between 1971 and 2015, more than 150,000 units of housing were created using the exemption, including as many as 37,000 affordable units (Husock and Armlovich 2015).

Over time, the program was modified through various stages. In 1985, 421a was amended to include the initial version of the GEA, which originally contained much of Manhattan bounded roughly by 14th and 96th Streets. Prior to the creation of the GEA, all residential development projects could receive 421a benefits as-of-right. After 1985, developments

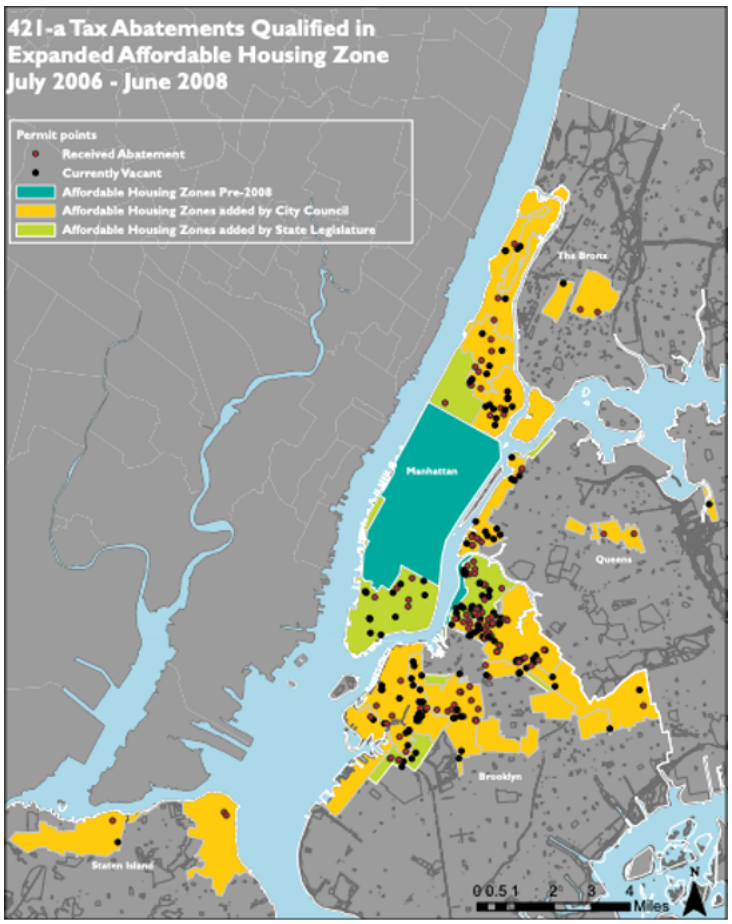
outside the GEA maintained as-of-right access to the program, but developments within the GEA were subject to restrictions on residential affordability. At the time, projects within the GEA were required to offer at least 20% of their housing units at affordable rents to low- and moderate-income families (up to 130% AMI), as certified by HPD, in order to be eligible for 421a benefits. This was the first explicit affordability requirement in the 421a program and was created to ensure that public investments in the highest-demand parts of NYC created benefits for residents across the class spectrum (Konopko 1987).

In the mid-2000s, with 421a up for renewal by the state legislature, major critiques of the program began to emerge. Between 2000 and 2006, New York City's average housing costs doubled, quickly creating a significant need for new affordable housing. Housing advocates argued that 421a benefits were being absorbed by market rate developers who were exacerbating this shortage. Many experts and community leaders criticized the effectiveness of the 421a program as a tool for creating new affordable housing (Husock and Armlovich 2015). While higher estimates placed the number of affordable units created by 421a at greater than 30,000, other analyses found that only about 5,000 of these units were truly affordable to low-income New Yorkers. Additional critiques emerged about the program's cost: due to the sheer volume of 421a recipients, the program was costing the City more than $750 million annually in foregone property tax revenue. Opponents argued that these funds could be better spent elsewhere, such as in the library system, welfare benefits, and transportation upgrades (Pratt Center 2011).

Based on rapidly-changing conditions in the housing markets and criticism from many sides, the Bloomberg administration formed a task force in 2006 to analyze potential changes to 421a. Among other recommendations, the task force concluded that the conditions that created the need for the original GEA in 1985 could be observed in many new parts of the city that, as of 2006, had no affordability requirements under 421a. In response to public critique and the Bloomberg administration's recommendations, 421a was reformed through a series of policy changes between 2006 and 2008 as part of its renewal by the state legislature.

These changes, centered around an expansion of the GEA, were implemented to expand 421a's effectiveness as an affordable housing program (Husock and Armlovich 2015). The New York state legislature voted to expand the GEA to include most of Manhattan and parts of Brooklyn and Queens in 2006. Shortly afterwards, the New York City Council moved to expand the GEA even further. The final expanded GEA, which took effect with the renewed 421a policy in 2008, included all of Manhattan as well as neighborhoods with high-demand real estate markets in the other four boroughs, as shown in figure 2.1 (Pratt Center 2011).

Figure 2.1: Boundaries of GEA Expansions, 2006-2008



Source: Produced by Pratt Center (2011)

The expanded GEA remained in effect for nearly eight years, from late 2008 until the program expired once again at the end of 2015. At that time, the state legislature replaced 421a starting in 2016 with the Affordable Housing New York Program (AHNY), a similar tax

exemption program that made several key changes in an attempt to mitigate criticisms of 421a. One of the main changes under AHNY was the outright elimination of the GEA. Once AHNY took effect, developments across the city were subjected to the same affordability requirements previously required only within the GEA under the 421a program (at least 20% of units affordable at or below 130% AMI) (421a Benefits Statute 2016).

2.2 Neighborhood Change in NYC

The effects and significance of 421a cannot be evaluated outside the context of neighborhood change and gentrification in NYC over the past two decades. Today, the social fabric of the city is defined in many ways by inequity across many core metrics. More than half (52.6%) of renters were rent burdened prior to the pandemic (spent >30% of income on rent); more than a quarter (28.1%) were severely rent burdened (spent >50% of income on rent). The top quintile of residents has an average annual income that is 27.9 times higher than the average income in the lowest quintile, the sixth-highest ratio among all large American cities[1] (Reiss et al. 2020). The New York metropolitan area is the second-most segregated among metro areas with at least a million residents. To perfectly integrate white and Black New Yorkers, 80% of these residents would have to move to a different neighborhood (known as the dissimilarity index) (Frey 2018).

Despite the efforts of city leaders and community advocates, neighborhood change since 2000 has largely worsened these issues rather than mitigate them. The proportion of renters that were rent-burdened increased by nearly double since 2000, when only 33% of renters paid more than 30% of their income on rent (Reiss et al. 2020). Income inequality grew even more: the average income in the top quintile in the early 2000s was 9.7 times higher than in the bottom quintile, nearly one-third of the same ratio in 2019 (Kazlovsky 2008). Racial segregation was the only metric to improve since 2000, with the Black-white dissimilarity

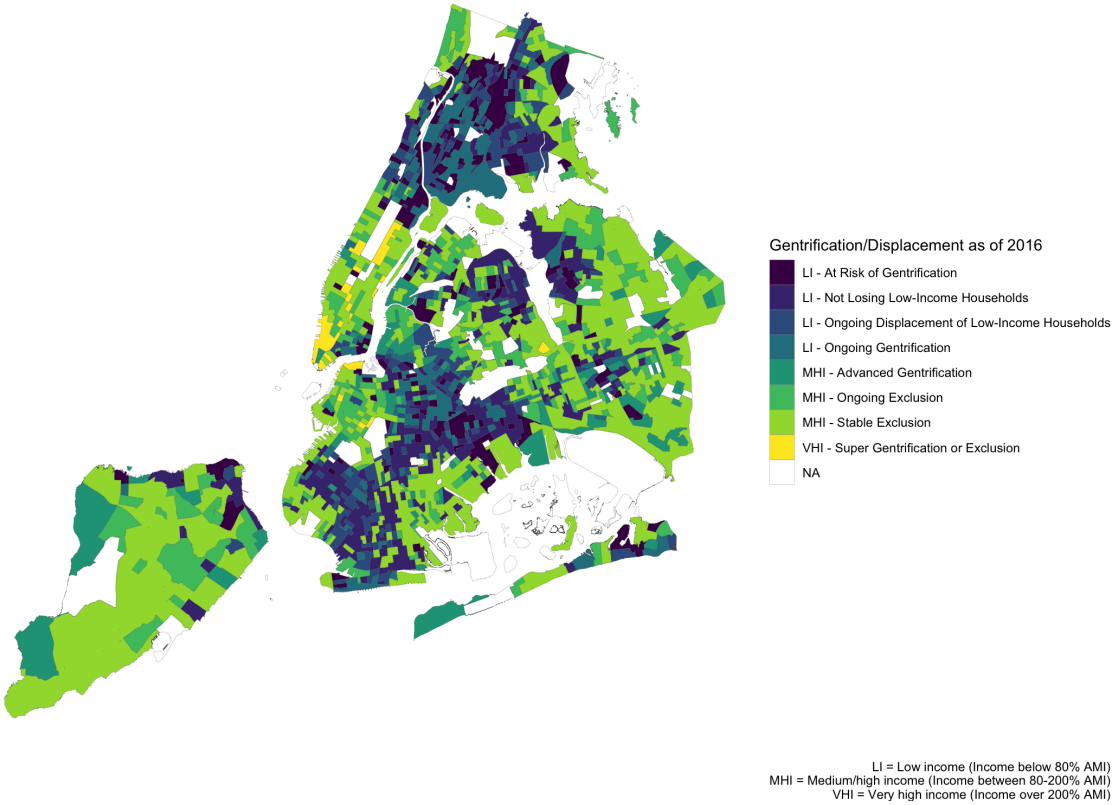
1. While similar, this metric is distinct from the 80/20 ratio analyzed in this paper; the 80/20 ratio considers only the cutoff points for the highest and lowest quintiles, rather than the average income within each quintile. The 80/20 ratio in the same year was 3.83 (see Methodology for data sources).

index (or the percentage of Black and white residents who would have to change neighborhoods to achieve perfect integration) decreasing by about 4% through 2017. However, racial segregation in metro areas across the country decreased far more over this same period; as a result, NYC jumped from the fourth-most segregated city in 2000 to the second-most in 2017 despite its marginal improvement in racial segregation (Frey 2018).

Gentrification and displacement[2] are significant challenges facing NYC today. Nearly half of Census tracts in NYC (1,017 tracts out of 2,165, or 47%) remained low-income as of 2016, defined by a median household income below 80% of AMI. However, 65% of these tracts (659 of 1,017) were either at risk of or already experiencing gentrification and/or displacement; over one-third of all low-income households in NYC lived in a gentrifying low-income neighborhood in 2016. An even larger number of tracts (1,070 tracts out of 2,165, or 49%) were already sufficiently gentrified by 2016 to be altogether financially inaccessible to low-income households (Urban Displacement Project, New York - Gentrification and Displacement). Figure 2.2 shows the spatial distribution of tracts by these metrics.

2. In this paper, gentrification refers to qualitative changes in a neighborhood's population (ie. increase in high-income, highly-educated, and/or white residents). Displacement refers to the forced movement of low-income residents and residents of color due to rising housing costs. While these trends often occur simultaneously, they are distinct and not inherently connected.

Figure 2.2: Gentrification and Displacement by Neighborhood Income, 2000-2019



Source: Data and metrics created by the Urban Displacement Project (New York - Gentrification and Displacement)

Accessibility is a particular concern related to gentrification in NYC. Low-income populations in NYC have historically lived in walkable neighborhoods with strong access to jobs. While this remains true today, gentrification is a significant threat to low-income residents' ability to live in these communities. Across the city, high-accessibility neighborhoods experienced a 20% increase in households making over $100,000 from 2000 to 2015; over the same period, households making less than $25,000 decreased by nearly 35% in these neighborhoods. As of 2017, nearly 45% of the city's high-accessibility tracts are vulnerable to displacement. This issue is experienced inequitably along racial lines. Across the New York metro region, high-accessibility neighborhoods that are vulnerable to displacement are 69% Black and Latino on average, compared with an average of only 26% across the rest of the region (Sanchez et al. 2017).

In the context of this paper, it must also be noted here that gentrification within the expanded portion of the GEA follows somewhat different trends from the city as a whole, as shown in table 2.1. The proportion of tracts that were low-income in 2016 was higher in the expanded GEA than the entire city (288 of 537 tracts, or 54%). However, 76% of low-income tracts within the expanded GEA (219 of 288) were experiencing or at risk of experiencing gentrification and/or displacement in 2016, significantly higher than the citywide figure of 65%. In all, the expanded GEA included 28% of all low-income tracts in the city in 2016, but 33% of low-income tracts that were gentrifying. This discrepancy suggests that low-income tracts within the expanded portion of the GEA experienced gentrification and displacement to a greater extent than their counterparts in other parts of the city from 2000 to 2016. However, the causes of the expanded gentrification and displacement within the expanded GEA are previously unknown and are therefore explored in this paper.

Table 2.1: Gentrification by Tract in New York City and the Expanded GEA, 2016

	New York City		Expanded GEA	
	# of tracts	% of tracts	# of tracts	% of tracts
Total Tracts	2165	-	537	-
Low Income Tracts	1017	47%	288	54%
Medium/High Income Tracts	1029	48%	184	34%
Very High Income Tracts	41	2%	15	3%
LI - At Risk of Gentrification	202	9%	73	14%
LI - Not Losing Low-Income Households	358	17%	69	13%
LI - Ongoing Displacement of Low-Income Households	250	12%	59	11%
LI - Ongoing Gentrification	207	10%	87	16%
MHI - Advanced Gentrification	117	5%	39	7%
MHI - Ongoing Exclusion	259	12%	62	12%
MHI - Stable Exclusion	653	30%	83	15%
VHI - Super Gentrification or Exclusion	41	2%	15	3%
Missing Data	78	4%	50	9%

Source: Data and metrics created by the Urban Displacement Project (New York - Gentrification and Displacement)

2.3 Impacts and Effectiveness of 421a

The impacts of the 421a program and the GEA expansion are less thoroughly researched than similar policies in other parts of the U.S. Throughout its history, the 421a program has been widely criticized as a 'trickle-down' handout to developers that is both expensive and ineffective (Cohen 2009). Critics point first to the enormous price tag: the program has grown to cost the City over $1 billion annually in lost property tax revenue (Neighborhood and Housing Development 2015). Despite this massive price tag, 421a provides a low return on investment with regards to incentivizing new housing development, especially affordable units. A recent study found that more than 93% of affordable rental units receiving a 421a exemption fiscally profited from the program, suggesting that the cost of the program to the City is greater than the cost of developing affordable units. Market-rate rental units, which cost developers less to create, profit to an even greater extent from the program (Stern, Willis, and Madar 2015). Condominiums receiving 421a benefits are no more efficient as a public investment: although condo buyers pay over $30,000 more for units with 421a exemptions than those without, the tax savings from the 421a exemption are far greater than the extra costs for these homeowners (Propheter 2017). As much of the financial benefit of the 421a program is transferred to property and condo owners rather than incentivizing housing development (especially affordable housing) that otherwise may have proven financially infeasible, the City is left footing a far larger bill than necessary to achieve the development goals of the program. According to the City's own estimates, this gap cost the City at least $2.3 billion in wasted investments between 2005-2015 (Propheter 2017).

Various studies have specifically examined the impacts of the 2008 GEA expansion on housing development and neighborhood change in the areas included within the expanded GEA. One study concluded that 421a projects in low-income neighborhoods within the expanded GEA created a significant amount of affordable rental units. However, 421a recipients in most middle- and high-income neighborhoods in the GEA were overwhelmingly

market-rate condominium developments. Overall, the study concludes, more than 80% of 421a expenditures after 2008 subsidized market-rate rental units and condos (Li 2015). Another study estimated that the cost of 421a to the City increased from about $750 million in 2008 to over $1 billion by 2013, yet only 8% of units receiving the exemption during that period had an affordable designation from HPD. The remaining 92% of subsidized units were market rate rentals and condos (Neighborhood and Housing Development 2015). Both of these analyses suggested that 421a did create some new affordable housing after the GEA expansion, but in a highly inefficient manner that largely subsidized wealthy homeowners and developers. These studies also did not analyze the extent to which new affordable units were located within neighborhoods that were part of the GEA expansion or compare these development trends to pre-existing patterns in the same neighborhoods.

In many other cases, however, analyses of the impacts of the GEA expansion are complicated and inconclusive. In the aforementioned studies, calculations of the locations, values, and affordability levels of 421a projects were often rough estimates due to the lack of central data on 421a properties (Li 2015; Neighborhood and Housing Development 2015). Another study found that household income increased more in the expanded GEA than in the rest of New York City between 2008 and 2015; however, it was not clear whether this change was a result of upward mobility among existing residents or displacement of those residents by wealthier newcomers (Hong 2016). Most recently, a team of NYU researchers concluded that physical proximity to the expanded GEA boundary had no impact on residential segregation as measured by Thiel's Entropy index (ie. neighborhoods closer to the new boundary, either within or outside the GEA, were no more or less likely to be segregated than those further away from the boundary) (Gao et al. 2021). This study was the first to consider the impact of 421a on neighborhood change indicators using a spatial discontinuity regression, which considered the relationship between distance from the GEA boundary and racial entropy. However, this study only considered spatial proximity to the GEA boundary at a single point in time. It did not account for potential differences in longitudinal trends as a result

of changing policy requirements under 421a. The exclusive focus on geographic distance as an independent variable also fails to consider categorical differences within and outside the GEA; it is plausible that the two spatial categories contained different trends and outcomes even if spatial distance from the GEA boundary was not a significant predictor. Given the shortcomings and lack of clear conclusions in previous studies, significant research is still needed to understand the impacts of the GEA expansion on affected neighborhoods.

Chapter 3: Methodology

3.1 Methodological Approach

In this paper, I implement a mixed-methods analysis of the 421a GEA expansion to document potential impacts of 421a on key neighborhood outcomes. I first conduct a comprehensive policy analysis of affordable housing policies in New York City and across the country to place the 421a program in policy context. Through this analysis, I also extract trends in similar policies to identify potential impacts of 421a based on precedent in similar external contexts. Informed by this analysis, I then deploy a two-model statistical analysis of longitudinal quantitative data at the Census tract level in New York City from 2000-2019. Through this analysis, I extract numerical trends in neighborhood outcomes in relation to the GEA boundary, compare these results with conclusions from other policy analyses, and identify correlational and causal relationships between the GEA expansion and changes in key outcomes.

3.2 Qualitative Methods

In chapter 4, I utilize a policy analysis to review the affordable housing policy landscape in New York City, New York State, and across the United States to extract conclusions on the potential impacts of 421a. I first review prior literature broadly focused on affordable housing analysis and establish a theoretical framework through which my analysis will operate. This framework is intended to organize the broad range of affordable housing policies in the American context in order to determine which geographic and policy contexts may be comparable to the 421a program. After establishing this framework based on previous literature, I then conduct a review of other affordable housing policies at the city, state, and

federal levels to document the context in which 421a operates. Finally, I review literature examining the impacts of other policies that share theoretical similarities to 421a in order to establish a set of potential impacts that 421a may have based on precedent in other localities and policy contexts. While these studies are not based on 421a specifically and their conclusions may or may not be applicable to this program, trends from similar policies can guide hypotheses about the likely outcomes of 421a and shape the context for the quantitative impact analyses conducted in chapter 5.

3.3 Quantitative Methods

Based on the conclusions drawn from the policy analysis, I then turn to a quantitative modeling analysis to draw specific conclusions about the impacts of 421a on neighborhoods in New York City. To do this, I collect data from 2000-2019 on seven outcome variables determined by areas of potential impact identified in the policy analysis. I implement two models (described below) to determine correlational and causal relationships between 421a and output variables, using the GEA expansion as a spatial proxy for isolating the impacts of the affordability requirements of 421a on affected communities in NYC. In each model, I also normalize for 24 input variables including basic neighborhood demographic information to minimize spurious relationships and specifically draw out the significance of 421a on each outcome.

3.3.1 Quantitative Methodological Precedent

A wide body of literature has attempted to measure the spatial impact of place-based policies across many disciplines. The methodological approaches of this literature merits consideration because of the experimental challenges such research must consider. Unlike randomized-controlled experimental methods for determining causal relationships, policy researchers frequently do not have the ability to construct a controlled and randomized research environment. Instead, causal relationships between policy and outcomes in the

affected population must be estimated through quasi-experimental methods that seek to approximate a randomized experimental research design (DiNardo 2008). Among many such models that have been implemented in social science research, three were considered for this paper:

- **Regression discontinuity design (RDD):** First proposed by Thistlewaite and Campbell (1960), an RDD model analyzes the causal effect of an intervention by assigning a cutoff point in the target population and applying the intervention either above or below the cutoff. Researchers can then compare outcomes in participants close to the cutoff point and use differences in these outcomes on either side of the cutoff point to estimate the effects of the intervention. The cutoff point is frequently chosen based on policy requirements; for example, age-based policies can be analyzed through an RDD model that uses the policy's age threshold as a cutoff and tracks outcomes in participants just above and just below that age. This model can also be applied to place-based policies by using the geographic boundary of the policy as the cutoff point and tracking outcomes in participants located close to this boundary; a recent analysis of the impacts of the GEA expansion used this model (Gao et al. 2021).

- **Interrupted time series design (ITS):** In an ITS model, researchers analyze time series data before and after an intervention to estimate the impact of the intervention. This model requires data for a given output to be collected in a given population for a substantial length of time prior to, and after, the intervention. The intervention point is used as a temporal cutoff; researchers analyze trends in the outcomes of interest before and after this cutoff, and differences in the outputs post-intervention are attributed to the impacts of the intervention. The internal validity of this model is based on the assumption that output trends prior to the intervention would be likely to continue without external stimulation, and changes immediately after the intervention can therefore be assumed to be caused by the intervention (Bernal, Cummins, and Gasparrini 2017).

- **Difference-in-differences (DiD):** Like the ITS design, DiD models use temporal data to estimate the impact of an intervention on output(s) of interest. Researchers identify a control and treatment group based on the application of an intervention, then gather data for each group over at least two points in time (one of which must be before the intervention and one of which must be after). Trends are analyzed for each group over time; the model assumes that the two groups demonstrated similar trends prior to the intervention and that pre-to-post-intervention trends in the control group would therefore be reflected in the treatment group were it not for the intervention (known as the parallel trends assumption). Therefore, any differences in the treatment group are attributed to the impacts of the intervention. This model was most prominently implemented by Card and Krueger (1994).

While these and other quasi-experimental methods can be a relatively effective way to measure the social impacts of policy, the shortcomings of such 'experiments' have also been well-documented. Much critique has been levied against the internal validity, or the level of confidence that a model's measurement of a causal relationship is reliable and not influenced by confounding factors, of these approaches. Among other potential internal shortcomings, all quasi-experimental models are vulnerable to selection bias in research subjects, inconsistency in group participants over time, and unstable measurement tools and processes (Campbell 1969). Furthermore, the internal assumptions of individual models, such as the difference-in-difference model's parallel trends assumption, may be challenging to prove reliably, leading to additional method-specific sources of internal invalidity (Rambachan and Roth 2021). External validity, or the extent to which results from these experiments can be accurately generalized to other settings and populations, is also a longstanding area of concern for social scientists. Atypical treatment settings and simultaneous interference by multiple treatments are among these external validity concerns that are most relevant for policy analyses (Campbell 1969). Despite these shortcomings, the inability to replicate policy interventions in a controlled and randomized setting necessitates the use of quasi-experimental

methods in many instances (DiNardo 2008).

I implement a DiD analysis in this paper to estimate the effects of the GEA expansion on neighborhoods across NYC. Although the RDD model is generally considered to most closely replicate the internal validity of a randomized-controlled experiment (Shadish, Cook, and Campbell 2002), this model requires a cutoff point that is attributed to some characteristic of the affected population, such as age or a geographic boundary. In this case, there is no single social indicator that can logically serve to divide the NYC population as it pertains to quantifying the impact of the GEA expansion. While proximity to the expanded GEA boundary could feasibly act as this cutoff point, similar recent research has already used RDD methods with the GEA boundary as the cutoff and found no conclusive relationship (Gao et al. 2021). Furthermore, my research does share the assumption in the aforementioned study that the distance of a given neighborhood from the GEA boundary has any relationship to changes in social indicators; rather, I am interested in average treatment effects across categorical (ie. GEA vs. non-GEA) groupings. Thus, I reject the RDD model for this study. I select DiD over an ITS model because the limited expansion of the GEA allows for a control group (neighborhoods that were not included in the GEA expansion) as a baseline for estimating counterfactual trends in the treatment group (neighborhoods that were not in the original GEA but were adopted into it under the 2008 expansion). ITS models are effective in cases in which a control group cannot be determined, but the presence of a control group allows for a higher degree of confidence in these counterfactual assumptions, therefore justifying usage here of the more robust DiD model (Benmarhnia and Rudolph 2019).

3.3.2 Description of Variables

In this study, I build a DiD model to estimate the impacts of the GEA expansion on seven output (dependent) variables in affected neighborhoods. This model considers 24 independent variables, including three descriptive dummy variables used to group neighborhoods and 21 baseline social indicators included to minimize confounding variable effects. All data

is collected at the Census Tract 2010 ("CT2010" or "CT") level for each of 12 years (2000, 2009-2019). I describe each of these variables in greater detail below. A full data dictionary can be found in Appendix A.

Independent Variables

Three independent variables are categorical dummy variables that are used to group CTs in the output model:

- **GEA (Treatment):** The GEA variable, also referred to as the Treatment variable, contains one of three possible values (as shown in figure 5.1):
  - *0:* CTs with a Treatment value of 0 were not included within the original GEA boundaries and remained outside the expanded GEA from 2009-2016. As these neighborhoods were never included within the GEA, this category serves as the control group in this model.
  - *1:* CTs with a value of 1 are those that were excluded from the original GEA, but were adopted into the GEA as part of the 2008 expansion. This category serves as the treatment value in this model.
  - *2:* CTs with a value of 2 were included within the original GEA boundaries drawn in 1985. Although not included within the DiD model in this analysis, these neighborhoods are included for EDA purposes to demonstrate pre-GEA expansion trends in those neighborhoods which were already subject to the GEA's affordability requirements prior to 2008.
- **Time:** The Time variable represents the temporal relationship of a given CT-year observation to the GEA expansion and contains one of three possible values:
  - *0:* Data captured before the GEA expansion (2000-2009) is given a value of 0[1].

1. Although the expanded GEA was adopted at the beginning of 2009, the ACS did not start reporting

  - *1:* Data captured after the GEA expansion but before the replacement of 421a with AHNY (2010-2015) is given a value of 1.
  - *2:* Data captured after the AHNY program replaced 421a and removed the GEA entirely (2016-2019) is given a value of 2. Although not included within the DiD model in this analysis, this data is included for EDA purposes to demonstrate trends in output variables after the retirement of the 421a program and the GEA.

- **DiD (Treatment-Time Interaction)**: The DiD variable is used in the model to isolate differences in trends in the post-expansion Treatment group of CTs. This variable was calculated by multiplying the **Time** and **Treatment** variables and contains one of two possible values:
  - *0:* Observations with a DiD value of 1 include data from all years in non-GEA neighborhoods (**GEA** = 0, **Time** = 0/1) as well as expansion neighborhoods during the pre-expansion period (**GEA** = 1, **Time** = 0).
  - *1:* Observations with a DiD value of 1 include data from GEA expansion neighborhoods during the expansion period (**GEA** = 1, **Time** = 1).

An additional 21 independent variables were included in the DiD model to account for any potential confounding relationships caused by pre-existing neighborhood indicators. These variables are as follows, grouped by category:

- **Population -** *Total Pop., Total Households*: The total number of residents and households in a CT.
- **Race/Ethnicity -** *White Pop., Black Pop., Asian/Pacific Islander Pop., Other Race/ Multiracial Pop., Hispanic/Latino pop.*: The number of residents in a CT that report

CT-level data until 2009, making the 2000 Census the last true pre-expansion year with available data. Therefore, in order to approximate pre-expansion longitudinal data trends, I was required to consider 2009 data to be pre-expansion. This challenge is discussed at greater length in the Limitations section.

each race and ethnicity. Given relatively low population densities in NYC, several Census race categories (Native American/Alaska Native, Two or more races, Some other race) were combined under *Other Race/Multiracial Pop.*; meanwhile, Asian population and Pacific Islander/Native Hawaiian population as reported by the Census were combined under *Asian/Pacific Islander Pop.*

- **Education -** *High School or Less, Some College or More*: The number of residents in a CT based on educational attainment. *High School or Less* includes all Census education categories resulting in a high school diploma, GED, or lower. *Some College or More* includes all categories in which a resident attended some college courses, including those that received any college degree as well as those that did not.

- **Age -** *Pop. Under 18, Pop. Ages 18-34, Pop. Ages 35-64, Pop. Ages 65 and Older*: The number of residents in a CT based on age.

- **Income -** *Median Household Income (MHI)*: The MHI of all households in each CT. This variable was normalized for inflation to reflect 2019 U.S. dollars.

- **Poverty -** *Pop. in Poverty, Pop. Near Poverty, Pop. Not in Poverty*: The number of residents in a CT based on poverty status. Residents that make less than the federal poverty line are considered to be in poverty, those that make between 100% and 150% of the poverty line are considered to be near poverty, and those that make more than 150% of the poverty line are considered to be not in poverty.

- **Rent Burden -** *Severely Rent Burdened pop., Moderately Rent Burdened pop., Non-Rent Burdened pop.*: The number of residents in a CT based on rent burden as defined by HUD. Residents that pay more than 50% of annual household income on rent are considered severely rent burdened, those that pay between 30% and 50% are considered moderately rent burdened, and those that pay less than 30% are considered not rent burdened.

- **Migration -** *Local, Migrant*: The number of residents in a CT based on place of residence in the previous year. *Local* represents those that lived in the same house or CT the previous year; *Migrant* represents those that moved from a different CT, county, state, or country within the past year[2].

Dependent Variables

This analysis considers seven output variables. A separate DiD model was created to approximate the impact of the GEA expansion on each output variable in the CTs included in the expansion. The output/dependent variables used are:

- **Neighborhood change score:** A CT's change score is a quantitative estimate of the degree to which the social exclusivity in that CT changed from the previous year. This variable was proposed by Collins (2015) as a means of quantifying the social changes in a neighborhood's population that are associated with gentrification. This figure ranges from 0 to 1 and represents a percent change, with a higher value representing a higher degree of change in social exclusivity. Thus, higher values for this variable indicate greater levels of gentrification and are considered undesirable, while lower values represent a lower degree of gentrification. Change score is calculated using the following formula:

$$abs(\Delta \text{pop}_{white} - \Delta \text{pop}_{black} + \Delta \text{pop}_{college} + \Delta \text{mhi})/4$$

where each Δ represents the percent change from the previous year[3].

2. The 2000 Decennial Census reports migration based on 1995 data rather than 1999; as a result *Local* and *Migrant* for the year 2000 represent the estimated number by dividing the each number as reported in the Census by 5.

3. This variable defines socially exclusive neighborhoods as those that have high proportions of white, college-educated, wealthy households relative to Black, non-college-educated, low-income ones. Of course, social exclusion has many characteristics that are not captured in this definition; however, the original author of this metric (Collins 2015) determines that these axes of displacement are among the most commonly-observed in American cities including NYC. This variable should therefore be interpreted as a proxy for neighborhood change and exclusion rather than a comprehensive measure of these outcomes.

- **Entropy index:** The Entropy index of a given CT is a multigroup measure of the degree of racial integration in that CT. First proposed by Theil and Finizza (1971), the Entropy index approximates the probability that a resident of a given geographic area will come into contact with members of other racial groups. Entropy can be calculated for as many racial or ethnic groups n as one desires; in this case, I use five categories (White, Black, Asian/Pacific Islander, Other Race, and Hispanic/Latino populations). A higher Entropy index represents greater racial diversity and is therefore the desirable outcome, while a lower value indicates less diversity and is undesirable. Since the Entropy index formula is log-based, the maximum value of this variable is $\ln(n)$; with five categories, the maximum Entropy index in this study is $ln(5)$ or approximately 1.6. Entropy index is calculated using the following formula:

$$\text{Entropy}_i = -\sum_{j=1}^{n} \text{p}_{ij} \ln(\text{p}_{ij})$$

where n is the number of racial and ethnic groups and i is a given CT.

- **Gini coefficient:** The Gini coefficient, also known as the Gini index, is a statistical measure of the degree of income inequality within a CT. The Gini value ranges from 0 to 1 and can be interpreted as a percentage of the amount of income inequality: a value of 0 indicates a perfectly-equal income distribution, while a value of 1 represents a perfectly-unequal distribution and is considered undesirable. The ACS provides a Gini coefficient for each CT beginning in 2010. For the years 2000 and 2009, I impute a Gini estimate using the following formula:

$$A/(A+B)$$

where A is the line of perfect equality (slope of 1) and B is the Lorenz curve representing the actual distribution of income.

- **80/20 ratio:** The 80/20 ratio is the ratio of the 80th income percentile in a given CT to the 20th percentile. For example, a CT in which the 80th income percentile is $100,000 and the 20th percentile is $25,000 would have an 80/20 ratio of 4. Higher values of this indicator represent a greater level of income inequality and are considered undesirable. As with the Gini coefficient, the ACS provides this value for CT beginning in 2010, so I impute an estimate for 2000-2009 by estimating the 20th and 80th income percentiles and calculating the ratio.

- **Geographic mobility:** A CT's geographic mobility score is the percentage of residents in that CT that lived in the same CT the previous year. A higher mobility score represents a higher degree of residential displacement and is considered undesirable. As the number of local and migrant residents are also independent variables in this model, the mobility score for each CT was calculated by simply calculating the number of migrants as a percentage of the total number of residents.

- **Local renter affordability index:** The local renter affordability index is an estimate of the probability that a resident of a given CT in NYC could find an affordable rental unit within that same CT. This variable ranges from 0 to 1 and is an approximation of the degree to which a neighborhood's housing stock meets the affordability needs of its current population. A higher value represents a greater probability that residents can afford to live in their own neighborhood and thus indicates a lower risk of displacement. Conversely, a lower value indicates a greater risk of displacement and is considered undesirable. This index is calculated based on an rental-oriented adaptation of the Homeownership Affordability for Renters Index (HARI) proposed by Goodman, Li, and Zhu (2018), which is a similar metric that estimates the probability that a renter in a given neighborhood could afford to purchase a home within that neighborhood.

The local renter affordability index is calculated using the following formula:

$$\sum_{i=1}^{n}(\mathrm{p}_i * (\sum_{j=1}^{i} \mathrm{u}_{ij}))$$

where i represents a given income band, p_i represents the probability of a renter's income falling into that income band, and u_{ij} represents the probability that a rental unit affordable to someone in that income band can be found within the neighborhood.

- **Citywide renter affordability index:** Similar to its local counterpart, the citywide renter affordability index is an estimate of the probability that a resident currently living anywhere in NYC could find an affordable rental unit within a given CT. Whereas the local index represents the degree to which a neighborhood's housing stock is accessible to local residents, the citywide index is an approximation of the degree to which the housing stock in a given neighborhood is accessible to the broader population of the city. A higher citywide value indicates that a neighborhood is accessible to more NYC residents and thus indicates that the CT is less exclusive or gentrified. A lower value indicates a higher degree of gentrification and exclusion in a CT and is considered undesirable. The citywide renter affordability index is calculated using a similar formula to the local index:

$$\sum_{i=1}^{n}(\mathrm{pc}_i * (\sum_{j=1}^{i} \mathrm{u}_{ij}))$$

where pc_i represents the probability of a citywide renter falling within income band i.

3.3.3 Data Collection & Processing

To facilitate the quantitative analyses in this study, I conducted a robust data collection, preparation, and consolidation process. Data was collected at the Census tract level for the years 2000 and 2009-2019. I gathered data from the following sources[4]:

4. Specific data sources and tables for each variable can be found in Appendix A.

Table 3.1: Quantitative Data Sources

Dataset	**Data Provider**	**Years Used**	**Data Tables Used**
Decennial Census	U.S. Census Bureau	2000	Summary file 1: P001, H013, P003, P004, PCT017, P012 Summary file 3: P056, P087, H069, P037, P052, P024
American Community Survey (ACS) 5-year estimates	U.S. Census Bureau	2009	B01003, B11001, B03002, B19013, B06012, B25070, B05003, B21001, B16004, B15002, B19001, B07003
American Community Survey (ACS) 5-year estimates	U.S. Census Bureau	2010-2019	B01003, B08202, B03002, B19013, B06012, B25070, B06001, B06009, B19083, B19080, B07010
Comprehensive Housing Affordability Strategy	U.S. Department of Housing & Urban Development	2000	B4, B6
Comprehensive Housing Affordability Strategy (CHAS)	U.S. Department of Housing & Urban Development	2009-2018	T15C, T17B
TIGER/Line shapefiles	U.S. Census Bureau	2000, 2010	Census tract
Relationship files (2000 to 2010 Census tracts)	U.S. Census Bureau	2010	
421a Geographic Exclusion Area approximate borders	The Municipal Art Society of New York	2009	

Neighborhood Indicator Collection

Data from the decennial Census and the American Community Survey was collected through the *get_decennial* and *get_acs* functions in the *tidycensus* package in R. This package allows API calls to the Census Bureau that indicate the years, geographic levels and boundaries, and variables of interest for each year. I created a master variable table with the codes for each variable in each year and passed this table as an argument to the API. Data was systematically collected for each year and Census tract within New York State using a looped R script, then filtered to only include tracts within New York City.

Data from the CHAS database was manually downloaded on the HUD website at the tract level for all of New York State. For the year 2000, tables B4 and B6 were used. CHAS reclassified its data tabulations starting in 2006; for 2009-2019, tables 15C and 17B were therefore used to gather the same information. Although all four tables contain cross-tabulations with additional variables, each also contains relevant information about housing affordability. Tables B4 and 15C include number of households at each HUD AMI level in a given tract, while Tables B6 and 17B estimate the number of rental units offered at each AMI level. To normalize this data, I read each downloaded data table in to R, filtered the data to only include tracts within New York City, and classified each observation by the AMI band. AMI levels were grouped into four bands based on the level of granularity available in the dataset:

- **Extremely low income:** Households making up to/units affordable at or below 30% of HUD AMI
- **Very low income:** Households making between/units affordable between 30% and 50% of HUD AMI
- **Low income:** Households making between/units affordable between 50% and 80% of HUD AMI
- **Moderate or high income:** Households making above/units affordable above 80% of HUD AMI

To remove additional variables cross-tabulated in the data tables and provide only an estimate of each desired output, I grouped each table by AMI band and aggregated the number of existing households and rental units within each band.

Geographic Data Preparation

In this paper, I use 2010 Census tract boundaries as the majority of data analyzed uses these boundaries. To prepare my geographic dataset, I downloaded the 2010 Census tract

boundaries from the Census Bureau's TIGER/Line Shapefiles database.

Within ArcGIS, I added this dataset as well as the approximate GEA boundaries shapefile provided by the Municipal Art Society. Because the GEA is drawn at the borough-block-lot (BBL) level, it is not perfectly compatible with Census tract boundaries. However, all neighborhood indicator data was collected by tract, so a tract-level approximation of the GEA boundaries was necessary for comparison. To create this approximation, I deployed a spatial calculation to identify all 2010 tracts within which at least 50% of lots were included within the GEA. Although this is not a perfect representation of the GEA, this approximation was used to capture tracts which were significantly impacted by the GEA without including tracts that had only a few parcels subject to GEA requirements. All tracts that did not meet these criteria were given a GEA classification of 0, indicating that they were excluded from the GEA prior to 2017. Finally, I used the Municipal Art Society's GEA classification variable to determine whether to classify each GEA tract as 2 (included within the original 1985 GEA) or 1 (included only within the 2009 GEA expansion).

The final geographic data layer was a shapefile containing the 2010 boundaries for each Census tract in New York City as well as the GEA classification variable.

Combined Dataset

I then created an R script to combine the separate data tables from each data source and year. To do this, I first utilized the Census Bureau's tract relationship files to reallocate data from 2000 and 2009, which was based on 2000 Census tract boundaries, to the 2010 tract boundaries. The relationship file provides a comparison multiplier for each 2000 tract to approximate the percentage of the population in that tract that is included within a given 2010 tract[5]. To carry out this comparison, I joined the relationship table provided by the Census to each data table based on the 2000 tract identifier. Aggregated variables

5. For example, if the area contained in Tract 1 in 2000 was redrawn such that 80% of the area was in Tract 2 and 20% was in Tract 3 in 2010, the multipliers in the relationship file would be 0.8 for the Tract 1 to 2 relationship and 0.2 for Tract 1 to 3.

(eg. population estimates) were multiplied by the provided comparison multiplier, grouped by 2010 tract classification, and added together. Meanwhile, proportional variables (eg. median household income, percentage of households in poverty) were grouped by 2010 tract classification and a weighted average was taken using the comparison multipliers.

Once this process was complete, I was left with a data table for each year and data source that contained information about each variable of interest at the 2010 tract level. To create the combined dataset, I simply joined each of these separate tables together into a single table. The final table contained an 2010 tract-level estimate of variable of interest for each year. I then joined this combined table with the geographic data layer, creating a spatial file that contained each input variable and GEA classification for each tract and year.

Calculating Output Variables

Once this combined dataset was created, I finally calculated the desired output variables for each tract-year observation using the formulas described in section 3.3.2. A full data dictionary for the combined table that was used for each of the statistical models described in the following sections can be found in Appendix A.

3.3.4 Proportional Odds Logistic Regression Analysis

The first of my two statistical analyses in this paper is a proportional odds logistic regression (POLR) model. A POLR model is defined as follows:

> "Ordinal logistic regression is a statistical analysis method that can be used to model the relationship between an ordinal response variable and one or more explanatory variables. An ordinal variable is a categorical variable for which there is a clear ordering of the category levels. The explanatory variables may be either continuous or categorical. [...] Ordinal logistic regression is an extension of logistic regression where the logit (i.e. the log odds) of a binary response is linearly related to the independent variables. If instead the response variable

> has k levels, then there are k-1 logits. A major assumption of ordinal logistic regression is the assumption of proportional odds: the effect of an independent variable is constant for each increase in the level of the response. Hence the output of an ordinal logistic regression will contain an intercept for each level of the response except one, and a single slope for each explanatory variable." (Parry 2016, p. 1)

Parry's definition effectively describes the advantage of POLR modeling. Whereas a linear model assumes a continuous relationship between the input(s) and output variables, POLR models produce a *stepwise* analysis that describes the relationship between the independent variable and each increase in the *level* of the output variable. In this paper, it is not known whether any of the input variables (including GEA classification) have a linear relationship with any or all of the output variables. Therefore, a POLR analysis has the desirable effect of describing these relationships in a less prescriptive manner.

The POLR model here is specifically used to answer my second research question:

> To what extent did these changes [in outcomes] differ in degree and/or direction within the GEA compared with the rest of the city?

Because POLR analyses show only the correlation between variables and do not consider causal relationships, I use this model only to estimate the correlation between a neighborhood's inclusion within the 421a GEA and its social outcomes.

Model Preparation: Reclassifying Outcomes

As stated in Parry's definition, POLR models require that the output variable is expressed in ordered levels rather than continuous numerical values. As each of the seven outcomes in this study are measured continuously by default, these values must be reclassified as ordered levels to facilitate the POLR analysis.

To meet this requirement of the model, I reclassified each output variable by its relative subjective favorability. To do this, I first converted each output variable to absolute quintiles (Lowest, Low, Middle, High, Highest). I then assigned a favorability label to each category. These assignments were based on a rough approximation of whether a higher or lower outcome in each variable would likely be considered the most favorable based on mainstream assumptions in the planning sphere. For example, planners tend to strive for urban communities with low levels of income inequality; therefore, a lower Gini coefficient would be considered more favorable than a high value. By contrast, racial integration is a typically desirable outcome, indicating that a higher entropy index is more favorable than a low one. I applied a similar approximation to each outcome variables and established favorability criteria for the analysis[6]:

- A higher value is more favorable for the following output variables:
  - Entropy index
  - Local rental affordability index
  - Citywide rental affordability index
- A lower value is considered more favorable for the following output variables:
  - Gini coefficient
  - 80/20 ratio
  - Neighborhood change score
  - Newcomers percentage

6. Of course, favorability is often more complex than a numerical value can express. For example, while improved racial integration is typically considered desirable by planners, a majority-minority community that becomes more racially integrated may in fact be a victim of gentrification, which most planners would classify as a harmful change. The classifications in this model are meant to fit the requirements of the model and roughly approximate the subjective implications of 421a, rather than serve as a definitive assessment of this relationship.

Based on these assumptions, I finally assigned a favorability level to each value based on its quintile band. Possible values were Most Favorable, Favorable, Neutral, Unfavorable, Most Unfavorable. This classification scheme was the basis of the ordered leveling required by the POLR model.

Collinearity Mitigation

Once each variable was reclassified into ordered levels by favorability, I then implemented a collinearity analysis to remove any independent variables with high similarity. To do this, I used a variance inflation factor (VIF) model, which approximates the degree to which each input variable in a model can be explained by other input variables. A high VIF score indicates that a variable is highly collinear in a given model and therefore weakens the model's statistical explanatory power.

To conduct this VIF analysis, I use the *vif* function of the *cor* package in R. This function accepts a linear model and returns a VIF score for each input variable[7] Based on recommendations from experts, I establish that any variables with a VIF score of 10 or greater should be excluded from my models (Vittinghoff et al. 2012).

I use a recursive R script to identify and remove any collinear variables for the model related to each output variable. I first pass all input variables and the output variable in question to the VIF function to determine a VIF score for each input. I then identify the input with the highest VIF score; if the score is greater than or equal to 10, I remove that input variable from the model and pass the remaining inputs back to the VIF function. This process is repeated until the highest VIF score in the model is less than 10, indicating that all input variables are sufficiently non-collinear. The variables included in this successful model are then stored for later use in the final POLR model. The VIF analysis removed the

7. It should be noted that this function is built on linear models; as previously stated, POLR models are nonlinear. However, no clear methodology or function exists for using a VIF-like analysis in ordinal models. Because each independent variable in this model is continuous, a linear model-based VIF analysis is an appropriate method to approximate collinearity even for nonlinear models (Senaviratna and Cooray 2019).

following input variables from each POLR model for high collinearity:

- College-educated population
- Local population (same neighborhood one year ago)
- White population

Final Model

Once the data was prepared for the model and collinear variables were identified and removed, I executed the POLR model for each output variable. To do this, I used the *clm* (coordinated link model) of the *ordinal* package in R and instructed the function to use a POLR model. I passed the seven output variables to the function one at a time along with the remaining (non-collinear) input variables. I then extracted the p-value, odds ratio, and standard error for each input in each model. Because the input variable of interest is the GEA classification and the other inputs are simply normalization variables, I stored only the statistical values related to the GEA classification variable.

The final value produced by these models is the odds ratio. This value estimates the odds that increasing the GEA classification variable (ie. comparing neighborhoods within the GEA to those outside of it) is correlated with a more favorable outcome. The odds ratio for each output variable is the figure that I use to approximate the general correlation from 2000-2019 between GEA inclusion and each outcome. The results of this analysis are displayed in chapter 5.

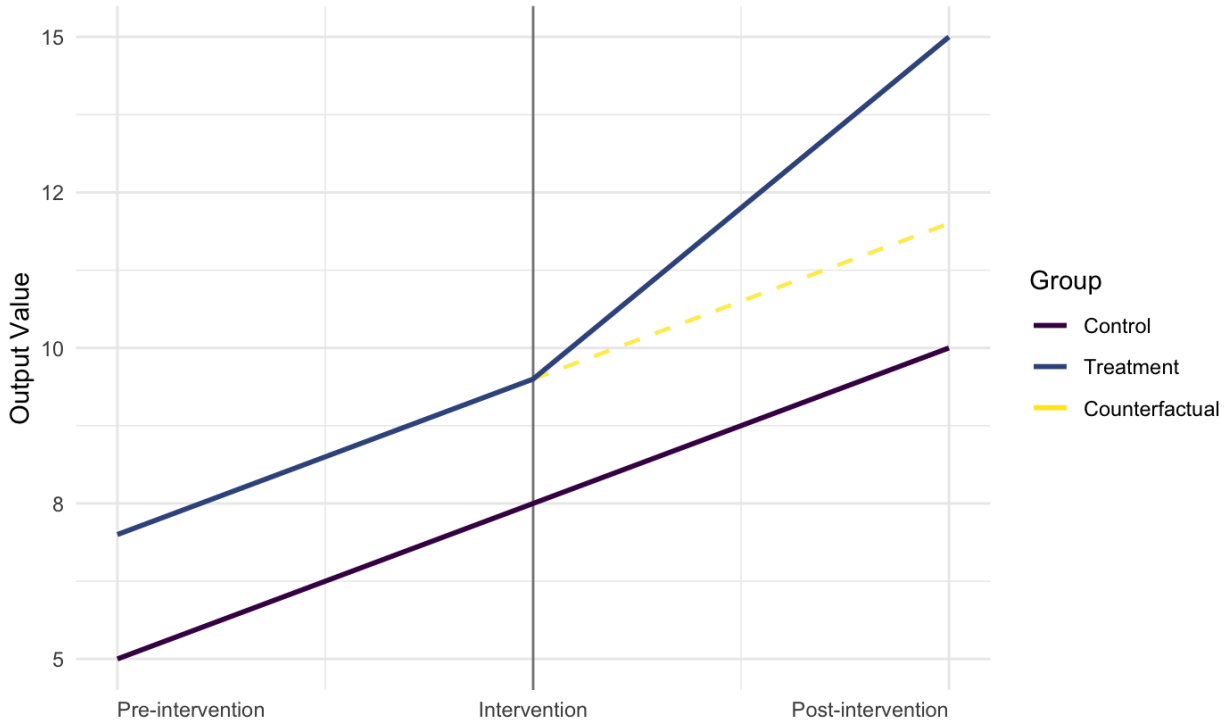
3.3.5 Difference-in-Differences Analysis

While the POLR model identifies the correlation between GEA inclusion and more or less favorable neighborhood outcomes, this analysis does not include a longitudinal component and cannot be used to draw causal conclusions. To accomplish this portion of the analysis,

I use a DiD longitudinal model. As previously described, DiD analyses are proven quasi-experimental models that can be used for purposes such as evaluating policy impacts in situations where direct experimentation is impossible.

DiD models approximate experimental methods by identifying control and treatment groups based on a given intervention. In this case, tracts that were incorporated into the 2009 GEA expansion are designated as the treatment group, while parts of the city that were never included in the GEA are the control group. Trends in each output variable are analyzed pre- (2000-2009) and post-intervention (2010-2016), with input variables used to normalize results based on pre-existing neighborhood characteristics. The DiD model assumes that, were it not for the 421a expansion, both groups would demonstrate parallel trends in each outcome. Therefore, any difference in outcomes between the control and treatment group is attributed to the causal impact of the 421a expansion. A theoretical example of this model is shown in figure 3.1.

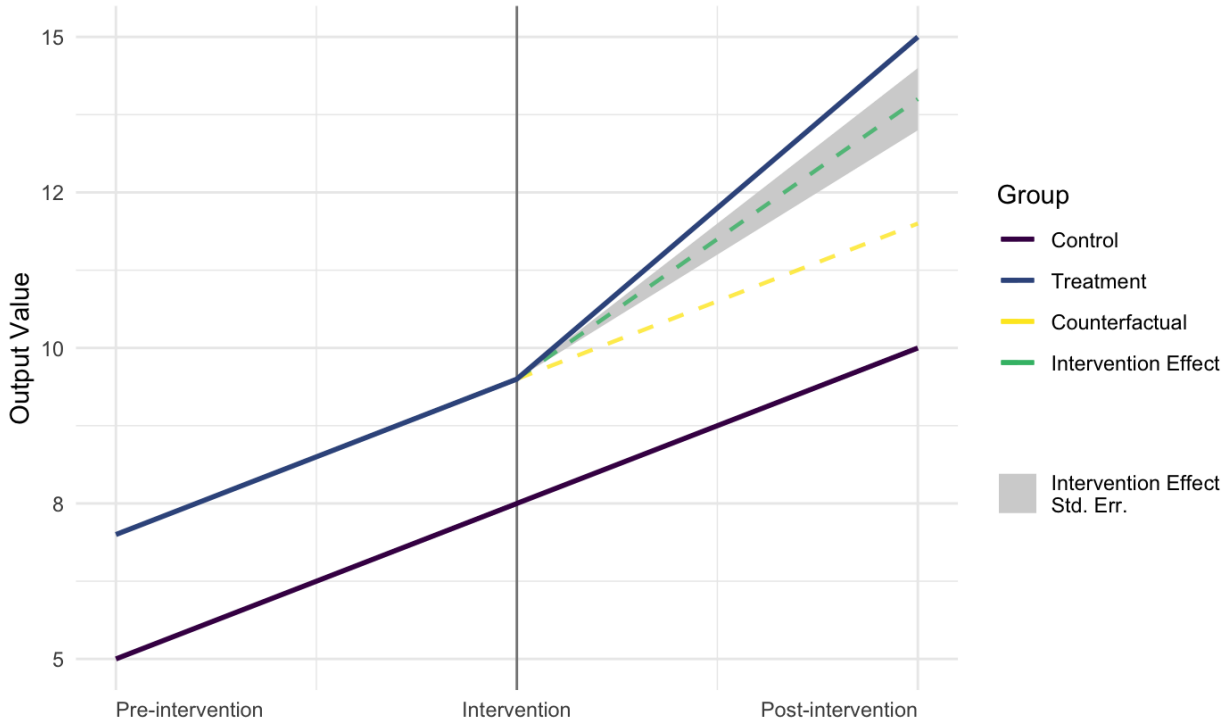
Figure 3.1: Basic Difference-in-Differences Model



In this example, the treatment group increases more rapidly post-intervention than the control group by 2.5 points despite displaying parallel trends prior to the intervention. Therefore, the policy intervention is attributed with causing an increase of 2.5 in the output variable in affected neighborhoods.

While this is the typical approach for a DiD model, I advance my analysis further by including a regression to normalize for the input variables in each model. Whereas a basic DiD model would attribute the entire difference of 2.5 in this example to the impacts of the intervention, the regression analysis can further the model's validity by estimating the extent to which that difference is actually attributable to the intervention as opposed to simply reflecting pre-existing differences in underlying neighborhood characteristics. Figure 3.2 shows a DiD model with an integrated regression analysis.

Figure 3.2: Difference-in-Differences Model with Regression



Whereas the basic DiD model concluded that the intervention had an effect of 2.5 on the output, the regression analysis reveals that the difference in outcomes is not entirely attributable to the effects of the intervention. According to the regression, the intervention is responsible for 1.5 points of the difference (with a 95% confidence interval of 1 to 2 points). The one remaining point of difference must therefore be attributed to changes in underlying characteristics and is therefore not a result of the intervention. This additional verification step is important in an analysis such as this study that is analyzing complex entities like neighborhoods that have many internal differences and are subject to many factors other than the policy intervention.

Data Preparation

Whereas the POLR model used the GEA classification dummy variable as the primary input variable of interest, the DiD model requires a new variable to indicate whether a given time-tract observation has been subjected to the intervention. This interaction variable then becomes the basis for the model. In order to meet this requirement, I filtered the data to include only the years 2000-2016 and only GEA classifications 0 (non-GEA) and 1 (expanded GEA). This focuses on the desired temporal and geographic scale by removing data after 2017, when all of NYC was subject to 421a's affordability requirements, and data from 2000-2016 in tracts within the original GEA that had already been subject to these requirements for more than two decades. I then add three new variables to this filtered dataset:

- **Time:** A dummy variable to indicate whether a given observation is from pre- or post-intervention. Data from 2000 through 2009 is assigned a value of 0 (pre-intervention), while data from 2010 through 2016 is classified with a value of 1 (post-intervention).

- **Treatment:** A dummy variable to indicate whether a given tract is part of the control or treatment group. Data from tracts outside the GEA is given a value of 0 (control group), while tracts included in the GEA expansion are classified as 1 (treatment group). *(This variable is identical to the existing GEA classification variable and was created solely for the sake of clarity.)*

- **DiD:** A dummy variable representing the interaction of the *time* and *treatment* variables. This is calculated by multiplying those variables together. Data from 2010 to 2016 within the expanded GEA therefore has a value of 1, while all other observations have a value of 0. This variable becomes the input variable of interest in the linear regression model.

Linear Trends Assumption Verification

A core element of the DiD model is the parallel trends assumption, which states that outcomes of interest demonstrated parallel trends in both the treatment and control groups prior to the intervention. Based on these trends, the assumed counterfactual outcome for the treatment group is that it would continue to follow the trends observed in the control group; any difference in these outcomes is attributed to the effects of the intervention (Mailman School of Public Health 2013).

To ensure the internal validity of the DiD analysis of the impacts of the GEA expansion, each output variable must demonstrate roughly parallel trends during the pre-intervention period (2000-2009). Prior to conducting the DiD analysis, I evaluate the extent to which each output variable meets the criteria for the parallel trends assumption. To do this, I calculate the averages in each variable for each year and compare slopes over time. While there is no black-and-white rule within DiD analysis for what slope constitutes a parallel trend, I assume that pre-intervention trends can have no more than a 10% difference between the control and treatment groups to meet this assumption. I therefore evaluate each variable to ensure that the trends from 2000 to 2009 meet this criteria.

Collinearity Mitigation

To prepare my data for use in the DiD model, I once again use a VIF analysis to identify variables with high degrees of collinearity. Since new input variables were added for the DiD model, I repeat the same steps from the POLR modeling process to identify highly collinear variables. As it turns out, the same three variables are removed from the DiD model for collinearity:

- College-educated population
- Local population (same neighborhood one year ago)
- White population

The remaining input variables are then passed onto the model.

Linear Regression

Once the collinear variables are removed, I then conduct a linear regression to estimate the quantitative impact of the GEA expansion (as measured by the DiD interaction variable) on each output. I use the *lm* (linear model) function from the *stats* package in R to execute this regression for each output variable. The model returns a coefficient, p-value, R-squared, and standard error for each input variable with respect to each output. Since the DiD interaction variable is the input of interest, I store these metrics for this input in each model. The DiD coefficient represents the model's estimate for the average annual difference in each output variable that is directly caused by the policy intervention when neighborhood characteristics are held constant.

DiD Model Integration

Finally, I conduct the integrated DiD analysis using the results of the linear regression. I first execute the basic DiD model as described above. To do this, I calculate the average of each output variable pre- and post-intervention, grouping by GEA classification. Next, I calculate the slope of the pre-to-post intervention change in the control group. I use this slope to calculate the counterfactual output within the treatment group and calculate the difference between this counterfactual and the actual observed outcome within the expanded GEA. This difference is the basic DiD model's estimation for the effect of the expansion on each output. To incorporate the additional regression analysis, I then extrapolate the linear model's estimation for the degree of impact of the expansion by multiplying each coefficient by seven (the number of years between 2009, when the expansion was implemented, and 2017, when the intervention period concluded). Finally, I compare this projection from the linear model with the difference between the observed and counterfactual outcome to produce an estimate of the degree of change in each outcome that can be statistically attributed to the

impacts of the expansion. The results of this analysis are displayed in chapter 5.

Chapter 4: Policy Analysis of 421a

4.1 Overview

Across the United States, affordable housing finance policies in the context of multifamily rental developments have been analyzed through many conceptual models. In this paper, I define a theoretical framework for grouping and analyzing American affordable housing policies[1]. Within my proposed framework, affordable housing policy models can be defined along two axes: the **direct beneficiary** of the program (tenants vs. landlords & developers) and the **program provision** (new development vs. lower housing costs in existing units). The former axis defines the target audience for the policy; while many affordable housing policies have benefits or incentives for both developers and tenants, one group is typically the primary beneficiary while the other receives indirect benefits. The latter axis considers the public benefit that the policy aims to provide. In general, affordable housing policies either seek to catalyze the development of new units that will be affordable from the start, or to facilitate lower costs within existing housing units (including the preservation of low costs in already-affordable units). This framework is shown in table 4.1, along with the placements of various major policies that are explored in greater detail within this section:

1. This framework was informed by conceptual models developed by Freeman and Schuetz (2017), Madden and Marcuse (2016), and Stein (2019).

Table 4.1: Affordable Housing Policy: Theoretical Framework

		Program Provision	
		New Development	*Lower Housing Costs*
Direct Beneficiary	*Developer*	Density/use bonuses Tax incentives (eg. LIHTC, **421a**) Inclusionary zoning Public loans/grants	HOPE IV Rental Assistance Demonstration (RAD) Project-based Section 8 vouchers NOAH preservation programs
	Tenant	Public housing Homeless shelters Transitional housing	Emergency Rental Assistance Program Housing choice Section 8 vouchers Rent control/subsidization Ground leases/community land trusts

Each cell in this matrix contains policies that, while different in many ways, approach the task of creating affordable housing in structurally similar ways:

1. **Market-Driven Affordable Development:** The top-left cell in this framework includes public efforts to catalyze new affordable housing development through the private market. Some of the programs provide incentives like tax reductions, density and use bonuses, and direct financing to developers in exchange for affordable housing creation. Others use requirements rather than incentives, including inclusionary zoning programs, through which municipal governments require market-rate residential developments to either set aside a portion of units as affordable housing or finance the creation of off-site affordable units. While the mechanism differs, each of these programs are efforts to divert public resources to real estate developers in order to create new affordable units. Today, this policy approach comprises the majority of public efforts to create affordable housing options (Stein 2019; Freeman and Schuetz 2017).

2. **Landlord Affordability Incentives:** The other group of developer- and landlord-facing policies includes those that focus on lowering housing costs or preserving already affordable units through investments and restrictions targeted at properties rather than tenants. Prominent examples here include federal initiatives such as the HOPE IV and Rental Assistance Demonstration ("RAD") programs, which utilize public finan-

cial incentives to facilitate the conversion of former public housing facilities to private affordable residences. These programs intend to remove public housing from government ownership and provide opportunities for physical improvements while preserving existing affordability guarantees. Other policies include project-based Section 8 vouchers, through which landlords can apply for federal funding to finance property improvements in exchange for providing affordability set-asides, and programs intended to preserve naturally-occurring affordable housing ("NOAH") through tax credits or other incentives to landlords (Madden and Marcuse 2016).

3. **Public Provision of Housing:** Once the backbone of American affordable housing provision, public efforts to directly provide affordable housing have fallen out of favor in modern planning circles. These efforts originated with the provision of public housing via the New Deal's Public Works Administration in 1935, but declined in ensuing decades due to a complex set of issues that is well-researched and will not be directly explored in this paper (Rothstein 2017). Today, public housing has largely been replaced in the policy sphere by other federal programs such as RAD, Section 8, and LIHTC. However, there are still over 930,000 public housing units across the U.S. that are home to more than 1.7 million residents (HUD, Picture of subsidized households). Modern examples of this policy approach include publicly-maintained homeless shelters and transitional housing, which are important to the small number of households that can access them but are not intended as a scaleable mitigation strategy for affordable housing shortages.

4. **Direct Assistance & Cost Reduction:** Finally, some public programs aim to offset or lower housing costs through initiatives that directly target and benefit tenants. Many of these programs include direct financial assistance for low-income households. Section 8 housing choice vouchers, which can be used by eligible households to cover housing costs beyond what the household is capable of paying, are by far the most

prevalent offering in this category. While large numbers of eligible households are unable to access Section 8 vouchers because of limited availability, the program subsidizes over 4 million households and 7.2 million residents across the country (HUD, Picture of subsidized households). This category also includes public efforts that directly maintain affordable housing costs through restrictions on property owners (distinct from programs like RAD and project-based Section 8, which incentivize owners to maintain affordability rather than requiring them to do so). Rent control and subsidization are common such policies through which municipalities restrict the degree to which landlords can increase rent on an annual basis. While more than 180 cities and municipalities have some form of rent control or stabilization, these are concentrated in only five states (NY, CA, MD, NJ, MN) and the District of Columbia. Two states (OR and CA) have implemented statewide rent stabilization, but 37 states prohibit any form of rent control (National Multifamily Housing Council 2022; Ramakrishnan, Treskon, and Greene 2019b).

In this paper, I define developer-facing affordable housing policies (categories 1 and 2) as the **neoliberal suite of affordable housing policy**. This builds on prior literature that defines many of these approaches as "trickle-down" housing policies as they direct public resources to typically wealthy developers and property owners in hopes of indirectly stimulating housing that is affordable to low-income renters (Cohen 2009). In this section, I describe the policy context surrounding 421a by analyzing contemporary neoliberal affordable housing policies in New York and across the United States. Through this analysis, I consider the ways and extent to which outcomes from comparable policies can serve as a lens of evaluation for 421a's impact on affordable housing development and neighborhood change in NYC.

4.2 421a in Policy Context

4.2.1 Other Policies in NYC

The 421a/AHNY program is part of a large slate of public affordable housing development programs offered by the City and State of New York. Several other property tax exemptions and abatements[2] are administered by HPD are offered in addition to 421a:

- **Article XI:** The Article XI tax incentive (Article XI HPD Term Sheet 2019) was created by the New York State Private Housing Finance Law to fund the construction or rehabilitation of affordable housing in New York City. Article XI exemptions may cover full or partial property tax burdens and last for up to 40 years. To be eligible for these benefits, properties must be owned by a Housing Development Fund Corporation ("HDFC"), a corporation created for the explicit purpose of developing affordable housing.

- **J-51:** The J-51 tax incentive (J-51 Benefits Statute 2021) is an as-of-right property tax exemption and abatement for residential rehabilitation and conversion projects. J-51 offers both a tax exemption (generally 34 years for affordable projects and 14 years for others) and a tax abatement (8.33 to 12.5 % for up to 20 years) to eligible projects. The J-51 program is set to expire as of June 30, 2022, requiring projects to complete construction by that date in order to receive the program's benefits.

- **420c:** Like 421a, 420c (420c Benefits Statute 2021) is a section of the New York State Real Property Tax Law that offers property tax exemptions to eligible developments in New York City. Tax exemptions under 420c may cover full or partial property tax burdens and are offered to properties that are dedicated to providing low-income housing. Eligible projects must be controlled by a non-profit or charitable organization,

2. Tax exemptions directly reduce the tax liability owed by a given property by a certain percentage or dollar amount. Tax abatements reduce the assessed taxable value of a property, thereby indirectly decreasing the tax liability.

are subject to HPD-approved regulatory agreements, and must be currently or formerly financed using federal low-income housing tax credits.

Aside from these property tax incentive programs, New York City offers many other affordable housing development programs that provide low-interest financing, grants, density bonuses, and other incentives to affordable projects. The most prominent of these initiatives are the Voluntary and Mandatory Inclusionary Housing programs (VIH/MIH):

- **VIH** (Inclusionary Housing Zoning Resolution 2018) was enacted in 1987 to incentivize affordable housing development in dense neighborhoods on a voluntary basis. Developments that opt in to this program must be located in R-10 Districts or Inclusionary Housing Designated Areas. Eligible developments receive a density bonus in return for the construction, substantial rehabilitation, or preservation of permanently affordable housing.

- **MIH** (Inclusionary Housing Zoning Resolution 2018) was enacted in 2016 as an obligatory extension of VIH that is triggered when medium- and high-density areas are rezoned, either through neighborhood rezonings or private rezoning applications. In locations where MIH is triggered by such rezonings, new developments or rehabilitations that create more than 10 units or 12,500 square feet of residential space are required to meet the program's affordability requirements. These requirements may be met through several options, each of which mandates a percentage and level of residential affordability. The most popular options require either 25% affordability at 60% AMI or 30% affordability at 80% AMI.

Finally, HPD and its partner finance agency, the NYC Housing Development Corporation ("HDC"), offer several opportunities for affordable housing developers to pursue grants and low-interest loan and bond financing for rental developments:

- **Extremely Low- and Low-Income Affordability Program (ELLA):** The ELLA program, offered as separate initiatives under HPD (ELLA HPD Term Sheet 2020)

and HDC (ELLA HDC Term Sheet 2018) intended to be used in tandem, is the City's primary direct funding mechanism for the construction of new low-income multifamily developments. The HPD program requires that at least 80% of units are affordable at or below 80% AMI, with the remaining 20% of units affordable below 100% AMI; the weighted average affordability of all units may not exceed 54%. HDC's supplementary funding has stricter requirements: these funds are restricted to developments with at least 100 units (although developments with 50-99 units may be considered at HDC's discretion), and all eligible units must be affordable at or below 60% AMI. HPD's funding offers between $122,500 and $137,500 per dwelling unit ("DU"), while HDC offers a up to $65,000 per DU and a maximum of $15 million per project. Both subsidies are offered as 30-year low-interest balloon mortgages; the balloon balance is due at loan maturity, although developments have the option to defer this payment further in return for extended affordability. In addition to these subsidies, HDC also offers a low-interest first mortgage for qualified projects on a 30-year amortization schedule.

- **Mix & Match Program:** Like ELLA, the mixed-income Mix & Match program is offered in tandem by both HPD (Mix & Match HPD Term Sheet 2020) and HDC (Mix & Match HDC Term Sheet 2018), in this case to fund the construction of new, mixed-income, multifamily rental projects. For HPD's funding, between 40% and 60% of units must be affordable below 80% AMI with the remaining units affordable below 120% AMI. HDC requires 40% to 60% of units to be affordable below 60% AMI with the remaining units affordable below 130% AMI. HPD offers a sliding subsidy that ranges from $0 per DU for units at 130% AMI and $220,000 per DU for units reserved for formerly homeless individuals. HDC's subsidy offers up to $75,000 per DU and a maximum of $15 million per project. Like the ELLA program, HDC also offers a low-interest, 30-year first mortgage for qualified projects.

- **Neighborhood Construction Program (NCP):** The city-level NCP (NCP HPD Term Sheet 2016), offered exclusively by HPD, provides capital funding for the construction of new mid-sized infill rental housing projects up to 45 units. Qualified developments must offer all units at or below 165% AMI. Projects may receive a maximum subsidy of up to $100,000 per DU, as well as a $1 disposition cost for city-owned lots. This subsidy is offered as a 30-year balloon mortgage with the balloon due at maturity.

4.2.2 State and Federal Policies

New York State offers several financing and incentive programs administered by DHCR:

- **New Construction Program (NCP):** New York State's NCP (NCP DHCR Term Sheet 2018) (distinct from the aforementioned HPD program despite a shared acronym) provides subordinate financing for the construction or rehabilitation of affordable rental housing that advances one or more of the State's housing priorities. This includes projects that redevelop state- and municipal-owned lots, advance community revitalization, and/or are supported by the Downtown Revitalization Initiative. Qualified projects must offer at least 50% of units at or below 60% AMI and must sign a 30-year regulatory agreement. The maximum subsidy within NYC is $140,000 per affordable DU, offered as a 30-year interest-only mortgage.

- **Homes for Working Families Program (HWF):** HWF (NCP DHCR Term Sheet 2018) is a funding source for high-priority projects that may be used to supplement NCP projects. HWF funding is only available for projects that require a higher subsidy than the per DU maximum allowed under NCP. These projects may receive up to $125,000 per affordable DU at a maximum of $4 million per project.

- **Supportive Housing Opportunity Program (SHOP):** SHOP (SHOP DHCR Term Sheet 2022) provides gap financing for affordable housing developments that

offer on-site supportive services. Eligible projects must offer at least 50% of units at or below 60% AMI or an overall project average affordability not to exceed 80% AMI. SHOP utilizes either 9% LIHTC funds or Housing Finance Agency ("HFA") bonds; subsidies are limited to $150,000 per affordable DU for LIHTC-funded projects or $200,000 per residential DU for bond-funded projects. Funds are provided as an interest-only mortgage with a term of 30 to 50 years.

- **Middle Income Housing Program (MIHP):** MIHP (NCP DHCR Term Sheet 2018; SHOP DHCR Term Sheet 2022) is a funding supplement for primary developments funded through other initiatives including NCP and SHOP that include middle-income units available ato 60% to 130% AMI. MIHP provides up to $140,000 per middle-income DU and can be used for no more than 30% of units in a single project.

- **State Low-Income Housing Tax Credit Program (SLIHC):** Like the federal LIHTC program, SLIHC (SLIHC DHCR Term Sheet 2019) offers credits for New York State-level taxes to qualified affordable housing developers. However, SLIHC offers these credits to units affordable at or below 90% AMI, a significant increase over LIHTC's 60% AMI limits. SLIHC also only requires that 40% of units in a project meet these affordability requirements to receive the credit. The program offers up to $750,000 per development, with exact funding based on demonstrated need and a complex scoring formula.

At the federal level, the most prevalent affordable housing finance program is the LIHTC program administered by HUD (Low-Income Housing Credit 2020). LIHTCs are offered by HUD to state housing finance agencies, including DHCR, which in turn disperse credits to qualified developers. Developers that receive LIHTC benefits generally sell the credits to raise investment capital to construct and operate their projects. There are two levels of credits offered through the LIHTC program as a means of funding affordable housing developments. The 4% credit is available as-of-right to affordable housing developers and

covers approximately 30% of eligible development costs. The 9% credit is highly competitive and is awarded by DHCR through an application process; these credits finance roughly 70% of eligible costs. Overall, the LIHTC program costs the federal government nearly $11 billion annually, but is a funding source for over 90% of new affordable housing units across the country (Keightley 2021).

HUD also provides funding for affordable housing development through several other programs:

- **Federal Housing Trust Fund (HTF):** The HTF (Housing and Economic Recovery Act (2008) 2008) is a HUD-funded program to finance the construction and preservation of multifamily rental units that are affordable at or below 30% AMI. HTF offers subsidies up to $125,000 per affordable DU to qualified projects. HTF is administered in New York by DHCR.

- **Community Development Block Grant (CDBG) program:** CDBG funding (Housing and Community Development Act (1974) 2010), offered by HUD, is automatically available to any city with more than 50,000 residents, including NYC. Smaller cities and counties may qualify for CDBG funding through HUD formula-based grants. In 2021, NYC received a CDBG award of over $280 million, of which roughly 75% was allocated to HPD for the provision of housing services and other administrative costs (de Blasio 2020).

Although this paper focuses primarily on municipal affordable housing policies, the importance of federal programs in terms of shaping and financing local policies cannot be overstated. Nearly 75% of HPD's annual budget comes from federal funds, including CDBG allocations and other sources (Zangerle and Obichere 2021). LIHTCs fill funding gaps in most affordable housing projects in NYC, and the City's affordable housing incentive programs would be fiscally unviable without federal funding and LIHTC allocations (Schwartz 2019).

4.2.3 Policy Trends in American Cities

A wide range of municipal affordable housing incentive programs can be found across the United States. No centralized repository of these municipal programs exists, complicating efforts to track policy trends. HUD itself is notorious for not tracking projects it funds in a clear, comprehensive, and non-duplicative manner; states and municipalities are even more ad-hoc in their data management in this area (Bolton, Bravve, and Crowley 2014). Below, I synthesize a review of current literature and data to describe trends in several policy areas. Among other sources, I heavily reference a database maintained by the National Low Income Housing Coalition ("NLIHC") that tracks 311 active affordable housing programs in all 50 states and 70 cities (NLIHC, State & City Funded Rental Housing Programs). While likely incomplete, this resource offers a unique consolidation of policies that is useful for identifying national trends.

- **Inclusionary housing programs** (inculding MIH/VIH in NYC) are among the most common municipal housing policies. Housing advocates estimate that there are more than 1,000 inclusionary housing programs across the United States, including both mandatory and voluntary versions of the model (Wang and Balachandran 2021). These programs are fairly simple conceptually: developers of new residential projects over a certain size are required to set aside a certain percentage of units to be rent-capped at a pre-determined affordability level based on AMI level. In some cities, developers can instead pay an in-lieu fee to the city instead of developing these affordable units. These programs emerge across a range of city sizes and housing market conditions. On average, across the U.S., IH policies require a set- aside of 16% of housing units in new developments to be affordable to renters or owners earning 50-80% of the Area Median Income (AMI) (Wang and Balachandran 2021).

- **Capital & production programs** directly provide funding and resources to support the development of affordable housing units. Among 72 active municipal programs

tracked in the aforementioned NLIHC database, 49 include capital funding incentives across 26 states and 33 cities (NLIHC, State & City Funded Rental Housing Programs). Of these programs, 44 offer capital through low-interest bonds or loans and 14 provide direct grants to qualified projects[3].

- **Rental assistance programs**, similar to the federal Section 8 program, are the other category of programs tracked in the NLIHC database (NLIHC, State & City Funded Rental Housing Programs). The database lists 29 active direct rental assistance programs at the municipal level, including several that also offer capital and production incentives. Of these programs, 20 are wholly or partially targeted towards residents experiencing homelessness; meanwhile, 15 are available to the general population.

- **Rent control and stabilization programs** have regained popularity with municipal governments in some states after falling out of policy favor in the mid-20th century. More than 180 cities currently maintain some version of these programs, including recent adoptions in cities including Minneapolis and St. Paul, MN, the first policies of their kind in the Midwest (Ramakrishnan, Treskon, and Greene 2019b; Nesterak 2021).

- **Tax incentive programs** like 421a have grown immensely in popularity among municipal governments in recent years. However, tracking the quantity, location, and requirements of these programs remains extremely challenging given the high level of localization of such policies (Singh 2020). At least 37 states offer some form of state-level tax incentives for affordable housing developers, and most cities with dedicated affordable housing incentive programs use tax incentives as either a standalone program or a component of other initiatives like inclusionary zoning (NLIHC, State & City Funded Rental Housing Programs; Hedlund 2019).

3. This database does not list any municipal-level tax credit or relief programs, indicating potential data gaps.

4.3 Affordable Housing Incentive Policies: Impact and Effectiveness

Broadly, the neoliberal suite of affordable housing development incentive programs (including 421a) has been criticized as a fundamentally unproductive set of approaches to the challenge of producing affordable housing. Like the 421a program, these programs are often both extremely expensive and highly inefficient. Cities often spend large portions of their affordable housing budgets on programs that generally fail to produce more than a fraction of the desired number of affordable homes. Several other key critiques have emerged from analyses of these initiatives.

In the first place, many of these programs - such as LIHTC, subsidized bond and loan financing, inclusionary housing, and tax exemptions like 421a - largely offer benefits for a finite period of time in exchange for a guarantee of affordability. In many cases, this is because the benefits and requirements of such programs are tied to a financial burden on the development, such as a mortgage or property tax liability. The financial obligation is waived or subsidized through public actions (eg. low-interest loans, interest-only mortgages, tax exemptions, etc.) and used as collateral to ensure that the property owner maintains the agreed-upon affordability requirements. However, once the pre-determined benefits period expires, the city loses its leverage to enforce affordability requirements. As a result, property owners tend to have a high likelihood of removing the affordability restrictions and converting formerly-affordable units to market-rate ones (Freeman and Schuetz 2017). Some programs have attempted to combat this through financial structures such as interest-only balloon mortgages that are due upon permanent loan amortization unless a property agrees to extend the affordability requirements. However, in many cases, the potential profits from converting affordable units to market rate ones outweigh the added costs of a second mortgage term. This is especially problematic in thriving real estate markets such as NYC and the GEA, as this revenue gap is larger and property owners are therefore more likely to withdraw affordability guarantees regardless of the potential punitive measures.

Second, these programs generally define affordability restrictions based on HUD AMI levels. However, this methodology has proven to be highly problematic. Because AMI levels are calculated at the Metropolitan Statistical Area ("MSA") scale, which includes suburban areas, these figures frequently fail to represent the true affordability needs of low-income residents within cities like New York (Pohorelsky 2019). For example, the HUD-defined AMI for the NYC MSA is $107,400 for a family of three, yet within city limits (where the average household size is just under three people), the median household income is only $67,000 (HUD, New York City Area AMI; U.S. Census Bureau, New York City Housing characteristics). Such discrepancies have enormous impacts on the effectiveness of programs that quantify housing need using AMI levels - these programs inherently underestimate both the number of households in need of affordable housing and the required degree of affordability.

Gentrification is a concern as a potential side effect of programs focused on encouraging affordable housing development. Inclusionary housing policies - the most prevalent local affordable housing incentive program structure - have been linked with overall decreases in both residential affordability and new residential construction in many other cities. In many cases, the former outcome is a result of policies that are not sufficiently discretionary in how funding is allocated, leading the program to mostly subsidize market rate units rather than affordable ones. Inclusionary housing policies that offer lenient off-site development options and/or in-lieu fees are examples of potential culprits here, as both create ample room for developments to fiscally benefit from public funding without delivering affordable units to the target community or, in some cases, at all (Ramakrishnan, Treskon, and Greene 2019a). On the other hand, programs that are too strict with affordability requirements or fail to offer sufficient benefits to developers can cause residential development to slow or even stop altogether. Rent control is a notorious policy on this point; while the impacts and effectiveness of rent control are highly debated, research does indicate that such policies tend to reduce the overall residential development rate (Sturtevant 2018).

The implementation of these programs also frequently correlates with increased levels of racial segregation, likely because they tend to incentivize new affordable units to be developed in neighborhoods that are already disproportionately home to residents of color (Ramakrishnan, Treskon, and Greene 2019a). New York City's affordable housing programs have faced this challenge firsthand. Many affordable housing projects use a tenanting strategy with a heavy local preference in an attempt to convey the benefits to the local community and prevent gentrification and displacement. However, the extreme racial segregation of NYC complicates the implications of this preference system. Approximately 75% of housing units financed by the City between 2014 and 2017 were built in neighborhoods with a majority of Black and/or Latino residents, a result of many factors including higher financial need in these areas as well as greater resistance to affordable housing construction in majority-white communities (Goldenberg and Cheney 2018). As a result, NYC's affordable housing development strategy has empirically demonstrated the unintentional side effect of exacerbating racial segregation rather than mitigating it (Beveridge 2019).

Finally, the neoliberal suite of affordable housing incentive programs has broadly been criticized for its contributions to the commodification of housing. In New York and many other major cities, the increased prevalence of real estate speculation as a financial investment in recent decades has led to the hyper-commodification of housing; not only are people's homes increasingly owned by external investors seeking to maximize profits, but so too are many other physical and social components of the housing system, including land, construction materials, labor, and tenant rights (Madden and Marcuse 2016). Many critics argue that affordable housing incentive policies overwhelmingly exacerbate this trend. Put simply, these programs are most effective when housing and the land upon which it is built are most valuable. Tax credits, from the federal LIHTC program to local incentives like 421a, are more desirable for developers when taxable property values are higher. Grant and loan programs, like many of those offered by HPD and DHCR, often seek to minimize the public cost of each project to maximize the number of projects that can be funded; as a result, projects

that can bring in more revenue from market rents are more viable funding recipients. Inclusionary housing and other programs that offer density bonuses in exchange for affordable set-asides are rooted in the assumption that the additional revenue from adding more units is more valuable to a developer than the cost to build them. In each of these cases and many others, neoliberal affordable housing policies are designed to work the best when the value of housing and all of its components is at its highest. Against the best intentions of planners and policymakers, these programs are in fact accelerating the very hyper-commodification of housing that necessitated them to exist in the first place (Stein 2019; Whitlow 2019).

Neoliberal housing programs like 421a have been created and promoted by planners across the United States as an alternative to public efforts to directly provide housing and direct financial assistance to those that need it. Despite offering the most direct and permanent affordability guarantees, once-dominant systems like public housing, rent control, and direct housing vouchers have fallen out of favor with urban leaders and policymakers that deride them as wasteful and unsuccessful uses of public funds. However, the neoliberal suite of programs that replaced them have fared little better, wrought with inefficiency and ineffectiveness. As a result, the affordable housing programs that are currently deployed across the U.S. are doing little to mitigate the housing crisis while arguably fueling the conditions and processes that caused it. In this, New York is no anomaly: despite the City's massive investment into neoliberal housing programs like 421a, the Section 8 voucher program is currently the most effective means of providing high-quality affordable housing in the city (Van Ryzin and Kamber 2002).

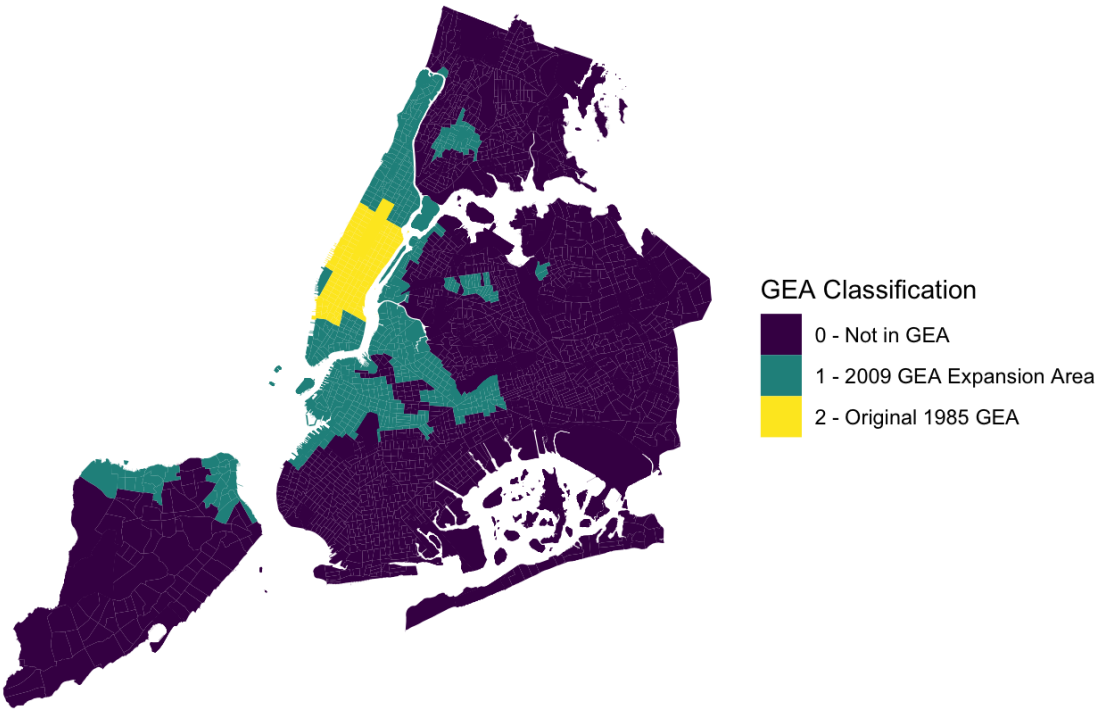
While this analysis of policy trends in New York and across the country is a useful tool for evaluating affordable housing programs like 421a, the extent to which the 421a program specifically follows or differs from national patterns is not fully known. In the next chapter, I implement a longitudinal data analysis, with the GEA expansion as a frame of reference, to examine the impacts and effectiveness of 421a as an affordable housing development tool.

Chapter 5: Quantitative Results

5.1 Exploratory Data Analysis

The GEA boundaries outlined in the 421a policy are drawn at a hyper-local scale, frequently encompassing individual lots and blocks. As the data used in this study is accessible only at the Census tract level, a CT-level approximation of the GEA boundaries was calculated. Figure 5.1 shows the GEA boundary assumptions used in this paper.

Figure 5.1: 421a GEA Tract-level Boundary Approximation



Each of the seven output variables tracked in this study was collected or calculated for the years 2000 and 2009-2019 at the CT level. Table 5.1 lists the citywide averages for

each output variable across the city, providing a baseline understanding of the degree and direction of trends in each variable. This data is shown in greater detail in table 5.2, which further breaks down the average indicator values to include data for each year and GEA inclusion status.

Table 5.1: Citywide Output Averages Across All Census Tracts, 2000-2019

Year	**Gini coefficient**	**80/20 Ratio**	**Change score**	**Entropy index**	**Local Renter Aff.**	**Citywide Renter Aff.**	**Newcomers**
2000	0.282	2.637	n/a	0.795	0.618	0.590	0.118
2009	0.279	2.575	0.299	0.723	0.544	0.512	0.111
2010	0.436	3.219	0.306	0.726	0.538	0.504	0.113
2011	0.439	3.254	0.186	0.739	0.528	0.499	0.116
2012	0.443	3.246	0.196	0.747	0.524	0.496	0.114
2013	0.447	3.297	0.185	0.753	0.517	0.491	0.115
2014	0.450	3.325	0.189	0.764	0.514	0.488	0.115
2015	0.453	3.265	0.172	0.768	0.508	0.484	0.111
2016	0.457	3.286	0.175	0.773	0.513	0.486	0.108
2017	0.457	3.340	0.158	0.781	0.516	0.488	0.105
2018	0.458	3.378	0.162	0.779	0.516	0.488	0.103
2019	0.461	3.383	0.134	0.840	n/a	n/a	0.099

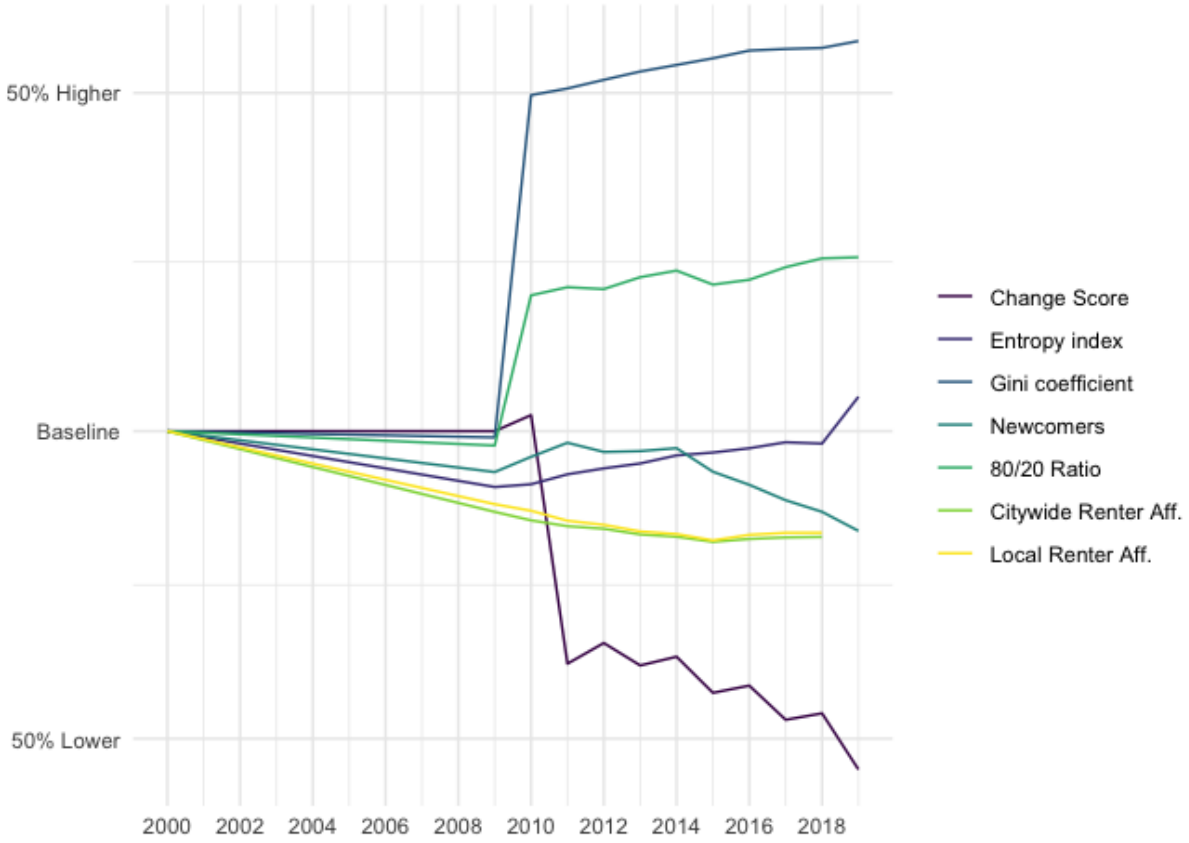
Table 5.2: Average Output Variables Over Time by Census Tract, 2000-2019

Year	GEA	Gini coefficient	80/20 Ratio	Change score	Entropy index	Local Renter Aff.	Citywide Renter Aff.	Newcomers
2000	0	0.28	2.58	n/a	0.78	0.60	0.58	0.11
2000	1	0.29	2.82	n/a	0.89	0.63	0.63	0.14
2000	2	0.33	2.62	n/a	0.69	0.76	0.51	0.17
2009	0	0.27	2.56	0.30	0.71	0.53	0.51	0.10
2009	1	0.28	2.70	0.31	0.80	0.55	0.54	0.14
2009	2	0.41	2.26	0.29	0.64	0.72	0.43	0.17
2010	0	0.42	3.03	0.36	0.71	0.52	0.50	0.09
2010	1	0.47	3.69	0.18	0.80	0.55	0.53	0.15
2010	2	0.53	3.71	0.16	0.69	0.70	0.42	0.19
2011	0	0.42	3.09	0.19	0.72	0.51	0.50	0.10
2011	1	0.48	3.62	0.18	0.82	0.53	0.51	0.16
2011	2	0.53	3.81	0.14	0.80	0.68	0.40	0.20
2012	0	0.43	3.09	0.21	0.72	0.51	0.50	0.09
2012	1	0.47	3.59	0.16	0.83	0.53	0.51	0.16
2012	2	0.54	3.80	0.14	0.70	0.69	0.40	0.21
2013	0	0.43	3.13	0.19	0.73	0.50	0.50	0.09
2013	1	0.48	3.69	0.18	0.83	0.53	0.50	0.15
2013	2	0.53	3.84	0.11	0.72	0.70	0.40	0.22
2014	0	0.43	3.16	0.20	0.74	0.50	0.49	0.10
2014	1	0.48	3.65	0.16	0.83	0.53	0.49	0.15
2014	2	0.53	4.03	0.12	0.74	0.69	0.39	0.22
2015	0	0.44	3.13	0.18	0.75	0.49	0.49	0.09
2015	1	0.48	3.58	0.15	0.84	0.53	0.49	0.15
2015	2	0.53	3.70	0.12	0.74	0.69	0.38	0.21
2016	0	0.44	3.13	0.19	0.75	0.49	0.49	0.09
2016	1	0.49	3.68	0.13	0.85	0.54	0.49	0.15
2016	2	0.53	3.69	0.13	0.75	0.69	0.38	0.20
2017	0	0.44	3.15	0.17	0.76	0.49	0.49	0.08
2017	1	0.49	3.82	0.13	0.86	0.54	0.49	0.14
2017	2	0.53	3.76	0.14	0.75	0.70	0.39	0.21
2018	0	0.44	3.16	0.17	0.75	0.49	0.49	0.08
2018	1	0.49	3.94	0.14	0.87	0.54	0.50	0.15
2018	2	0.53	3.83	0.13	0.75	0.71	0.41	0.20
2019	0	0.45	3.18	0.14	0.82	n/a	n/a	0.08
2019	1	0.49	3.91	0.11	0.93	n/a	n/a	0.13
2019	2	0.53	3.79	0.17	0.79	n/a	n/a	0.19

Across the city, the average Gini coefficient and 80/20 ratio increased from 2000 to 2019. Meanwhile, change score, newcomers percentage, and local and citywide rental affordability indices all decreased on average during this time. Entropy index declined between 2000 and 2009, but increased steadily thereafter. Figure 5.2 demonstrates the percent change relative to the year 2000 in each outcome variable, providing a visualization of these trends. Generally, these trends are exaggerated within the GEA; in a given year, tracts in the GEA

tend to have higher Gini coefficients, 80/20 ratios, and entropy indices, but lower values for change score, newcomers percentage, and local and citywide rental affordability indices.

Figure 5.2: Change in Average Neighborhood Outcomes, 2000-2019



5.2 Proportional Odds Logit Regression Baseline Model

A proportional odds logit regression (POLR) model was implemented to estimate the overall effects of inclusion in the GEA on neighborhood indicators, regardless of whether the neighborhood was in the original GEA boundaries or was incorporated into the GEA during the 2008 expansion. Table 5.3 lists the results of this model. The coefficient describes the quantitative correlation between GEA inclusion and each output; time is not a factor in this model.

Table 5.3: POLR Baseline Model Results: Impact of GEA Classification

Output	**Odds Ratio**	**P-value**	**Std. Err**
Gini coefficient	0.349	0.000	0.029
80/20 Ratio	0.604	0.000	0.027
Change score	1.072	0.008	0.027
Entropy index	1.169	0.000	0.026
Local Renter Aff.	1.098	0.001	0.029
Citywide Renter Aff.	0.886	0.000	0.029
Newcomers	0.917	0.000	0.029

The value of significance in this analysis is the odds ratio for each output. This value is the model's approximation of the likelihood that each output is more favorable within the GEA than outside of it. Values greater than one indicate that outcomes were more favorable within the GEA, while ratios less than one suggest less favorable outcomes within the GEA. For example, an odds ratio of 1.5 here would indicate that neighborhoods within the GEA demonstrated outcomes that were 150% more favorable than those outside the GEA. By contrast, an odds ratio of 0.5 means that a neighborhood within the GEA is only 50% as likely to have a favorable outcome compared with a demographically-similar neighborhood elsewhere. While this relationship is entirely correlational and does not denote causation, this ratio is useful for approximating the extent to which neighborhood change trends were more or less favorable in the GEA than in the rest of New York City from 2000 to 2019.

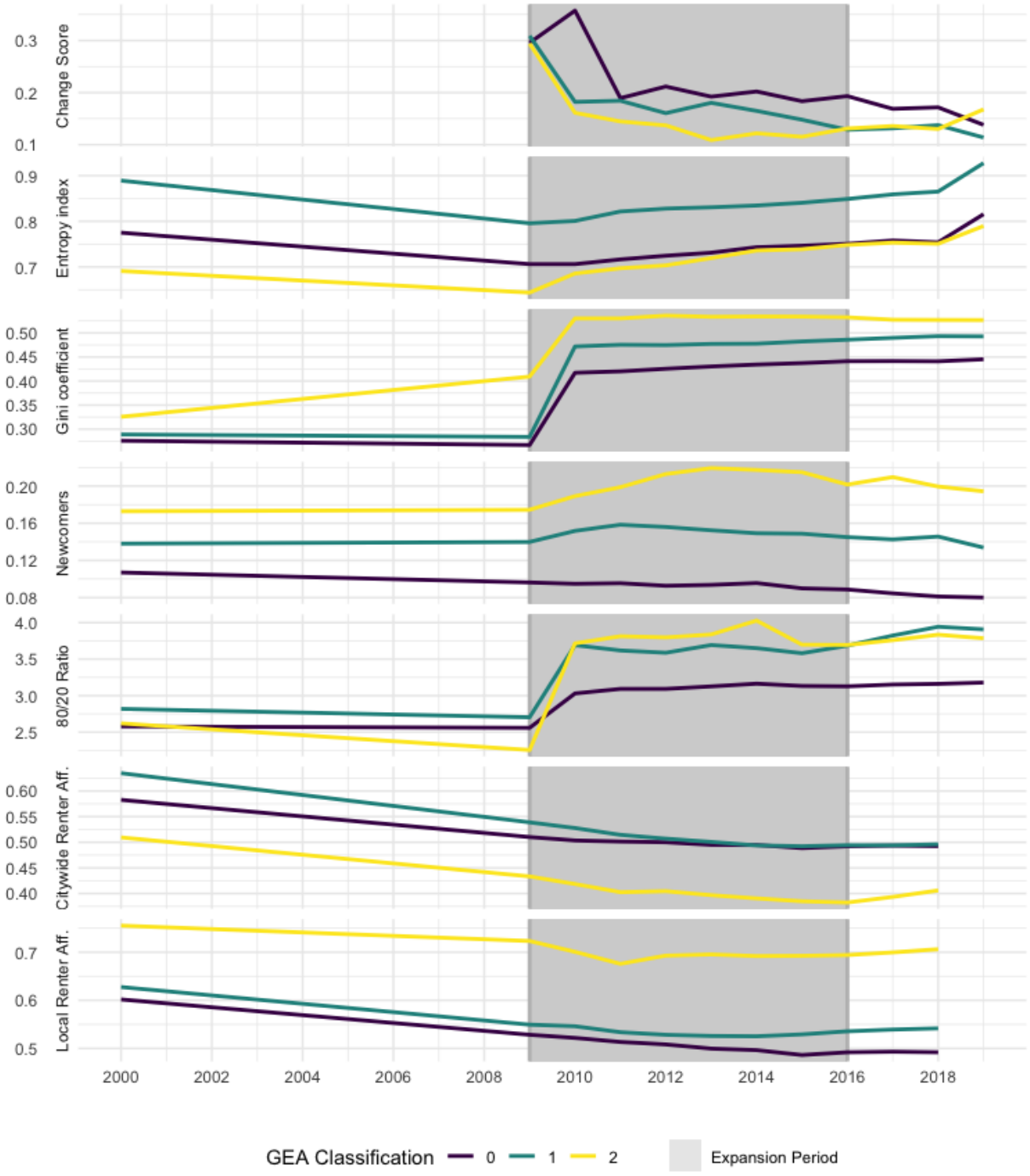
5.3 Difference-in-Differences Analysis

The parallel trends assumption is a key component of a DiD analysis, as described in chapter 3. Figure 5.3 demonstrates the average trends in each output from 2000 to 2019, with the GEA expansion period (2009-2016) highlighted in gray. Six of the seven variables

demonstrate parallel trends (defined as slopes that differ by no more than 10%) for GEA classifications 0 and 1 prior to the expansion, indicating that a DiD model based on this data will maintain internal validity[1].

1. Change score cannot be verified to meet the parallel trends assumption since data is not available prior to 2009. Results for this variable from the DiD model should be interpreted with caution.

Figure 5.3: Average Output Trends by GEA Classification, 2000-2019



While intended to verify the parallel trends assumption, this figure is also useful for visualizing absolute differences in outcomes by GEA inclusion. The GEA expansion area has

a higher average value in each outcome except change score than neighborhoods excluded from the GEA. While the difference between these two regions changes over time in each variable, the order of the relationship remains the same for all variables except the citywide rental affordability index, for which the expanded GEA has a higher initial average but is roughly equal, if not slightly lower, starting in 2012.

Given that pre-intervention conditions satisfy the parallel trends assumption, the DiD model estimating the impact of the GEA expansion on each neighborhood indicator was completed with results shown in table 5.4. The coefficient of interest in this table reflects the DiD interaction variable, ie. whether a given tract-year observation was within the GEA expansion or not. Therefore, the results of this table can be interpreted to specifically estimate the degree and direction of impact caused directly by the GEA expansion, regardless of pre-existing trends or population characteristics.

Table 5.4: DiD Model Results: Impact of GEA Expansion

Output	**Time/Treatment Interaction Coef.**	**P-value**	**R-squared**	**Std. Err.**
Gini coefficient	0.028	0.000	0.529	0.003
80/20 Ratio	0.360	0.000	0.150	0.045
Change score	-0.074	0.206	0.032	0.059
Entropy index	0.038	0.000	0.237	0.011
Local Renter Aff.	0.002	0.618	0.371	0.005
Citywide Renter Aff.	-0.011	0.007	0.386	0.004
Newcomers	-0.007	0.000	0.657	0.002

Table 5.5 lists the actual and predicted post-intervention average values for each output variable for expanded GEA CTs. The counterfactual prediction assumes that trends the expanded GEA would follow the same slope as areas outside the GEA. The DiD prediction extrapolates the coefficient assigned to the time:treatment interaction variable in the DiD

model and projects the final value if no other input variables were considered. This prediction can be interpreted as the model's approximation for the outcomes caused directly by the expansion of the GEA and excludes any variation caused by other internal and external neighborhood changes. Finally, the table lists the percent of the actual change that is predicted by the DiD coefficient.

Table 5.5: Explanatory Power of DiD Interaction Variable on Outcomes Within Expanded GEA

	Gini coefficient	**80/20 Ratio**	**Change score**	**Entropy index**	**Local Renter Aff.**	**Citywide Renter Aff.**	**Newcomers**
Pre-Intervention Actual Avg. Value	28.6%	2.76	30.9%	0.84	58.9%	58.7%	13.9%
Post-Intervention Actual Avg. Value	47.8%	3.64	16.4%	0.83	53.2%	50.4%	15.2%
Actual Change	19.1%	0.88	-14.5%	-0.01	-5.7%	-8.3%	1.3%
Counterfactual Avg. Value	44.4%	3.30	23.2%	0.83	52.6%	53.7%	13.0%
Counterfactual Change	15.8%	0.54	-7.7%	-0.01	-6.3%	-5.0%	-0.9%
Actual Change vs. Counterfactual	3.4%	0.34	-6.8%	0.00	0.6%	-3.3%	2.1%
DiD Predicted Avg. Value	47.3%	3.66	15.7%	0.87	52.8%	52.6%	12.4%
DiD Predicted Change	18.6%	0.90	-15.1%	0.03	-6.0%	-6.1%	-1.5%
Actual Change vs. DiD Prediction	0.5%	-0.02	0.7%	-0.04	0.4%	-2.2%	2.8%
% of Change Explained by DiD Variable	84.1%	100%	100%	0.0%	40.2%	33.7%	0.0%
% of Change Not Explained by DiD Variable	15.9%	0%	0%	100.0%	59.8%	66.3%	100.0%

Chapter 6: Discussion

6.1 Conditions and Trends in Neighborhood Indicators

The first research question addressed by this paper examines the pre-existing conditions and temporal trends in each of the seven neighborhood outcomes across NYC. This question is rooted in the hypothesis that a) New York City has generally become less affordable, more transient, more racially integrated, and more economically unequal since 2000 due to the effects of gentrification and displacement (trends based on existing literature); and b) these trends have been more exaggerated in parts of the city that were included within the GEA during the final six years of the program's existence, whether or not these discrepancies were caused by the program.

Writ large, the first half of this hypothesis is supported by the data analyzed in this analysis. Based on annual average values for each of the outcomes tracked in this study, several broad conclusions can be drawn. Income inequality increased substantially, with a 17.9% average Gini coefficient increase and a 74.6 point increase in the average 80/20 ratio. At the same time, housing affordability generally decreased, with the average renter being able to afford 10.2% fewer units in both their own neighborhood and citywide in 2018 than in 2000. Whether a result of decreasing residential affordability or other factors, neighborhoods generally experienced less population turnover from 2016 to 2019 than from 2000 to 2016. While the average neighborhood had a change score near 20% and an annual newcomer percentage of about 11.5% between 2011 and 2015, those figures declined to only 13.4% and 9.9% respectively by 2019. Finally, although the average Entropy index was higher in 2000 (0.795) than in any year other than 2019, the figure has steadily risen from 0.723 in 2009 to 0.840 in 2019, suggesting that the 2010s saw a general increase in racial integration across the

city. If these data accurately reflect trends in neighborhood change over the past two-plus decades, New York City is likely a less affordable and less economically equal place today than in 2000, though it may also be somewhat more residentially stable and integrated as well.

6.2 Neighborhood Change and GEA Classification

The second assumption in the aforementioned hypothesis - that neighborhoods within the GEA tend to experience these negative trends to a greater extent than those outside of it - is also largely supported by the data. Here, the results of the POLR model are useful to understand the extent to which a neighborhood's GEA classification correlates with social outcomes. Based on the POLR model (see table 5.3), neighborhoods that were included within the original GEA boundaries and the 2008 expansion demonstrated significantly worse income inequality metrics between 2000 and 2019. Neighborhoods in the GEA were only 35% as likely to have a lower Gini coefficient compared with neighborhoods outside the GEA; the likelihood for a more favorable 80/20 ratio was 60%, somewhat higher but still indicative of substantially worse outcomes within the GEA. Rent affordability was somewhat less conclusive: according to the POLR model, GEA inclusion correlated with a slightly higher likelihood of offering affordability to residents within the community (110% as likely as non-GEA neighborhoods), but less likely to be relatively affordable for those living in other parts of the city (89% as likely to be affordable as other neighborhoods). Neighborhood change demonstrated similarly mixed results. GEA neighborhoods were only 91% as likely as non-GEA areas to have a relatively high degree of year-to-year residential stability as measured by the percentage of newcomers. However, social exclusivity as measured by the change score was 7% more likely to be favorable within the GEA than outside of it. Finally, inclusion within the GEA correlated with a 17% higher probability of a neighborhood having a higher entropy index than a comparable non-GEA community. While this model does not consider temporality and should not be interpreted as a reflection of the degree or direction

of changes to these indicators, it provides a categorical 20-year snapshot of the city in which inclusion within the GEA correlates with statistically less favorable outcomes by some metrics (income inequality, citywide rent affordability, newcomers percentage) but more favorable by others (change score, local rent affordability, entropy).

6.3 Estimated Quantitative Impacts of the GEA Expansion

While the previous sections provide an important analysis of baseline conditions across the city, further analysis is needed to determine the extent to which the expansion of the GEA impacted these trends. This step provides an important distinction from the POLR analysis: while inclusion in the GEA categorically correlates with relatively better or worse outcomes depending on the metric, this does not necessarily support the assumption that incorporating a given neighborhood into the GEA will lead to better or worse outcomes. The POLR model is incapable of offering any evidence to suggest that less desirable social outcomes within the GEA are in any way caused by the 421a program. Many confounding factors, including pre-existing social conditions and concurrent policy interventions, may have created more or less favorable conditions within the GEA. The third research question in this study addresses this concern by focusing on the extent to which the expansion of the GEA altered the degree and direction of these neighborhood changes for those areas that were not included within the original GEA but were incorporated into it in the expansion.

The difference-in-differences model provides the opportunity to examine this question with the relatively high degree of causal certainty provided by quasi-experimental methods. Here, I examine each of the seven output variables through the results of this model to estimate the causal impacts of the GEA expansion. For each output variable, a figure is produced that shows the results of the DiD analysis for the impact of the GEA expansion on the outcome in affected neighborhoods. These plots include the pre- and post-intervention averages grouped by GEA classification and demonstrate five trend elements:

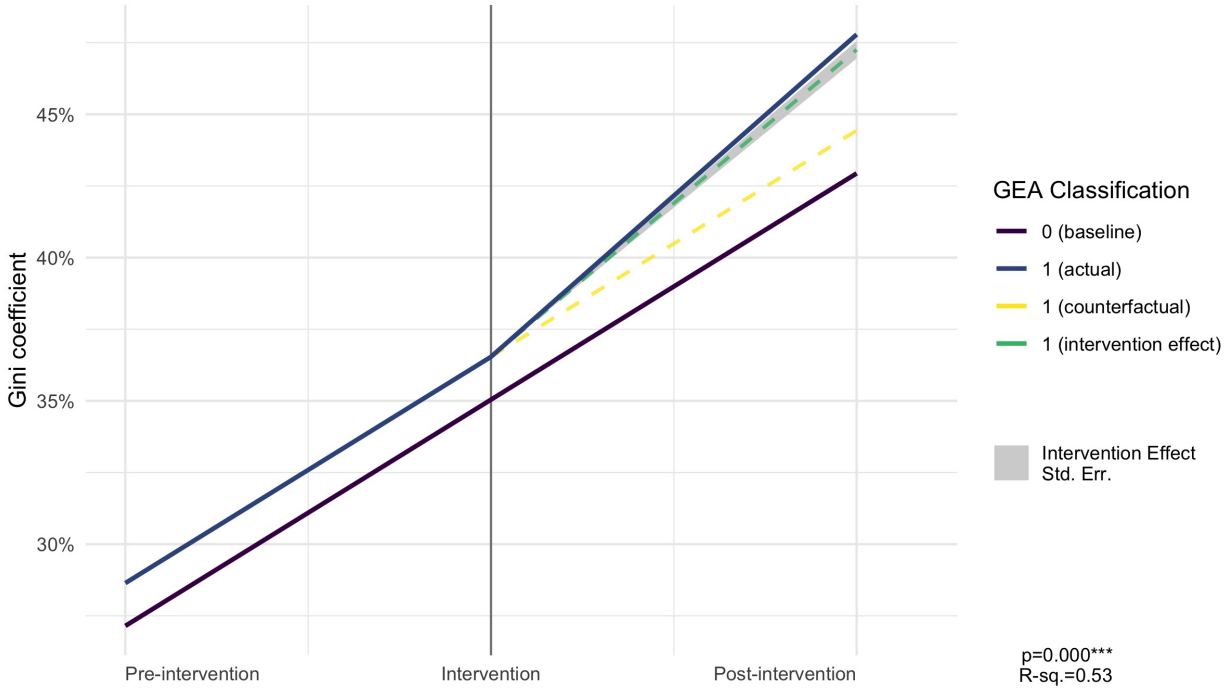
- **Baseline:** The average output trend across non-GEA CTs, which serves as the baseline

for approximating the counterfactual trends in expanded GEA areas.

- **Actual:** The actual average output trend in expanded GEA areas.
- **Counterfactual:** The anticipated counterfactual trend in expanded GEA areas based on the baseline areas. This projection assumes a parallel slope to the baseline condition.
- **Intervention effect:** The estimated effect of the time:treatment interaction variable on the output. This is the DiD model's approximation of the impact of the GEA expansion on the output in affected neighborhoods.
- **Intervention effect std. err.:** The standard error of the estimated intervention effect produced by the DiD model.

6.3.1 Gini coefficient

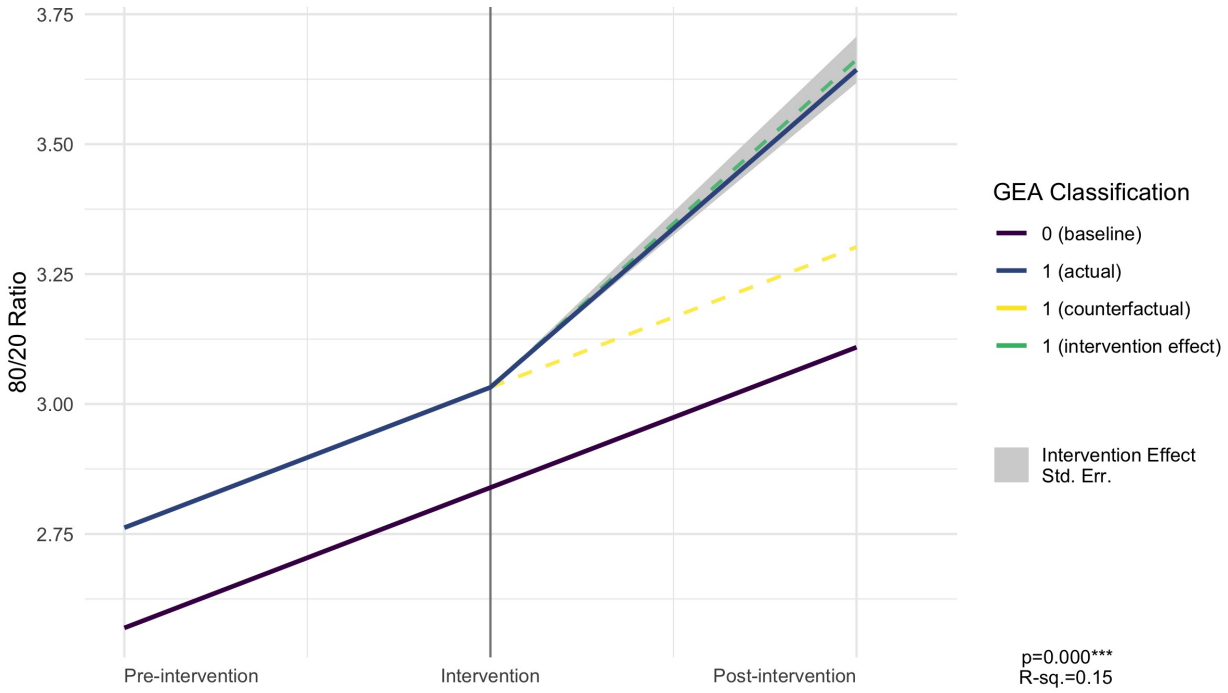
Figure 6.1: DiD Impact Analysis: Gini coefficient



The average Gini coefficient in GEA neighborhoods increased by an average of 3.4% more in the expanded GEA than the counterfactual prediction, as shown in figure 6.1. While neighborhoods across NYC experienced higher income inequality after the GEA expansion than before, this effect was higher within the boundaries of the expansion. The DiD interaction accounts for 97.4% of this difference with a small standard error (0.3%) and p-value ($p<0.001$). This model instead suggests that incorporating a given neighborhood into the GEA likely causes a faster growth rate in income inequality relative to areas that remain outside the GEA, a difference which is directly attributable to the effects of the GEA on neighborhood change. These results are supported by the POLR model, which indicated that GEA neighborhoods are much more likely to have a higher Gini coefficient than other parts of the city.

6.3.2 80/20 ratio

Figure 6.2: DiD Impact Analysis: 80/20 ratio

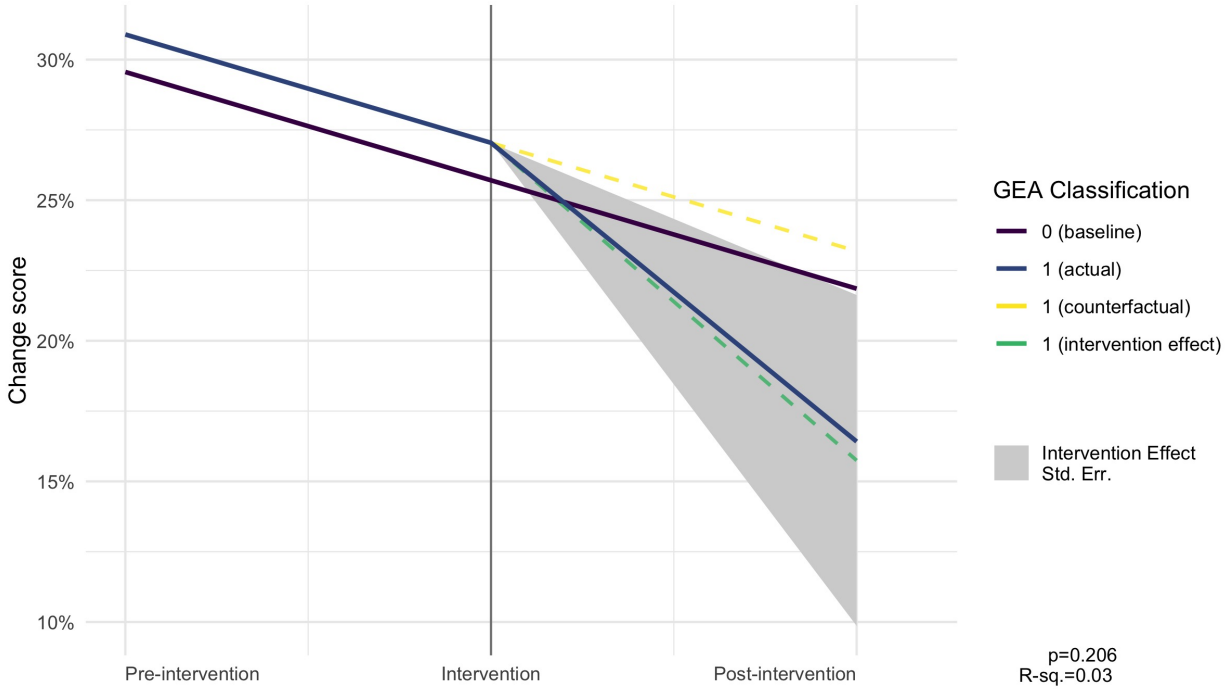


Results estimating the effects of the GEA expansion on CTs' 80/20 ratio were very similar to the Gini model, as shown in figure 6.2. The actual change in expanded GEA tracts again outpaced the counterfactual prediction, in this case by 0.34 points, indicating through a second metric that income inequality increased more rapidly within the GEA than outside of it after the expansion. The DiD variable accounts for 97.9% of this difference, though in this case the actual change underpaced the model's prediction, whereas Gini growth outpaced the model. With a similarly small standard error (0.05 points) and p-value ($p<0.001$), the results of this model suggest a significant causal relationship between incorporation into the GEA and an increased discrepancy between the earnings of low- and high-income residents. Once again, these results remain consistent with the POLR model; GEA inclusion tends to

lead to a greater income gap between the lowest and highest earners.

6.3.3 Change score

Figure 6.3: DiD Impact Analysis: Change score

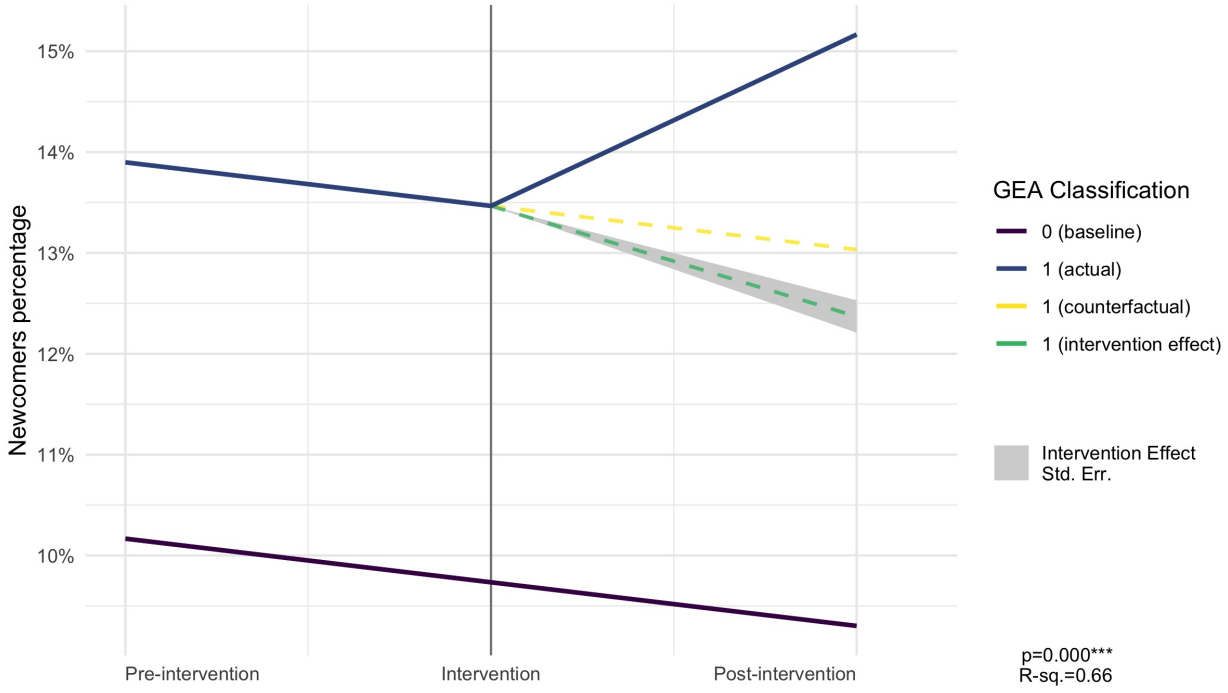


Unlike the Gini coefficient and 80/20 ratio, change scores for neighborhoods within the expanded GEA decreased far more quickly after the expansion than in external areas, shown in figure 6.3. As change score is designed to reflect gentrification and displacement, a lower relative value in this case indicates that GEA neighborhoods improved relative to baseline conditions over this period. The model estimates that the policy treatment accounts for 97.5% of this change relative to the counterfactual, suggesting a potential causal relationship. However, the high standard error (6%) and p-value (p=0.21) undermine the reliability of these results. Given the lack of any statistical significance of this relationship and the high margin for error, it is not possible to draw any definitive conclusions about the effects of

the GEA expansion on neighborhood change as measured by the change score. This is the first instance of a discrepancy between the POLR and DiD models: whereas the POLR analysis indicated that neighborhoods in the GEA had lower (more favorable) change scores than those outside, the DiD model fails to draw any causal relationship. The correlation identified in the POLR model may therefore be attributable to outside factors, underlying conditions, and/or other influences.

6.3.4 Newcomers

Figure 6.4: DiD Impact Analysis: Newcomers percentage

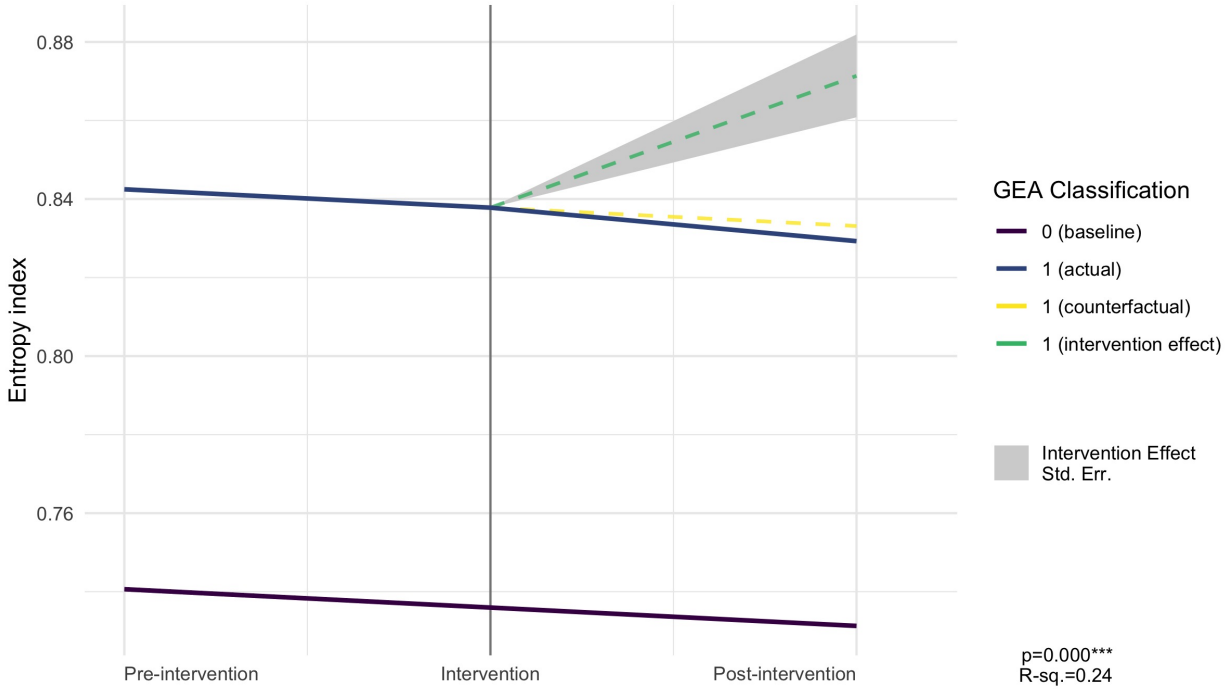


The DiD model for newcomers percentage produces unusually contradictory results related to the percentage of newcomers in a given tract, as shown in figure 6.4. On the one hand, the model suggests with a high degree of significance (std. err.=0.2%, $p<0.001$) that the GEA expansion leads to more desirable outcomes in affected neighborhoods. In this

case, the model estimates that incorporation into the GEA leads to a 0.9% decrease in the percentage of annual new residents in a given tract; accounting for existing conditions, neighborhoods in the expanded GEA would therefore be expected to see a 0.6% reduction in newcomers beyond the counterfactual assumption. Within an R-squared value of 0.66, this model is statistically the most significant of the seven outcomes. However, the actual percentage of newcomers in the average GEA tract increased by 2.2% relative to the counterfactual on average. The model unexpectedly produced predictions that were substantially different from demonstrated outcomes in not only degree but also direction. It is not immediately clear what caused the internal contradiction produced by this model. Given that the POLR model also indicated a strong relationship between GEA inclusion and a higher newcomer percentage, rather than the lower coefficient produced in this model, the validity of these results may be drawn into question.

6.3.5 Entropy index

Figure 6.5: DiD Impact Analysis: Entropy index

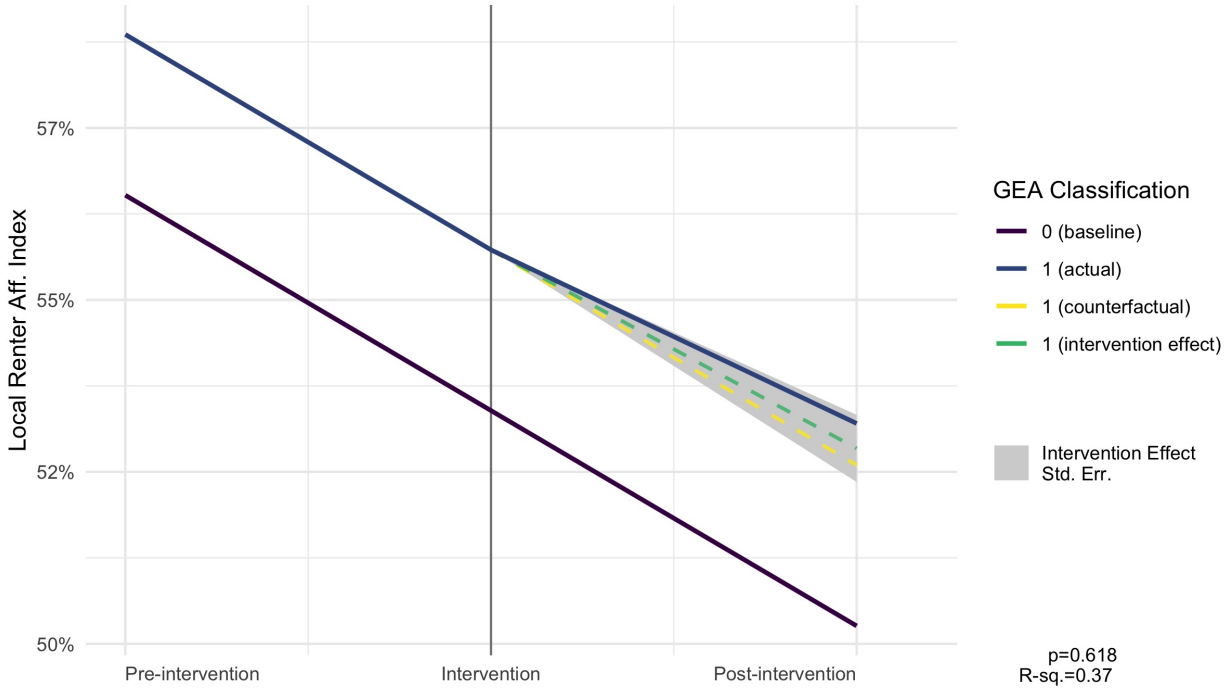


The DiD analysis similarly finds contradictory results, as shown in figure 6.5. On the one hand, the model appears to return strong results: incorporation into the GEA is associated with a 0.038 point increase (approximately 2.4%) in a neighborhood's Entropy index with strong statistical significance (std. err.=1%, p<0.001). Based solely on this model, it might be concluded that the policy effects of the GEA expansion led to significantly improved racial integration in affected communities. However, differences between actual reported data and the model's predictions create room for pause. Although the DiD treatment variable is statistically associated with an increase in a neighborhood's Entropy index, the average value in expanded GEA tracts actually decreased slightly more than the average non-GEA tract.

While this discrepancy may at first appear to threaten the validity of the DiD results, the statistical strength of the model raises the possibility that GEA incorporation did in fact have a positive influence on racial entropy in affected areas, but external factors nevertheless reduced the average Entropy index in these areas. One potential explanation here could be population size: the DiD model normalizes for population and thereby compares GEA neighborhoods to non-GEA areas of similar sizes. In such a direct comparison, it may be that GEA neighborhoods see a slower reduction in racial entropy than their non-GEA counterparts on average. However, since many of the city's most populous neighborhoods are in fact within the GEA, the average citywide decrease in racial entropy may be cumulatively felt more heavily within the GEA despite a more favorable per-resident entropy trend. Nevertheless, the lack of clear results from the model prevent any definitive conclusions from being drawn about the impact of the GEA expansion on racial integration.

6.3.6 Local renter affordability index

Figure 6.6: DiD Impact Analysis: Local renter affordability index

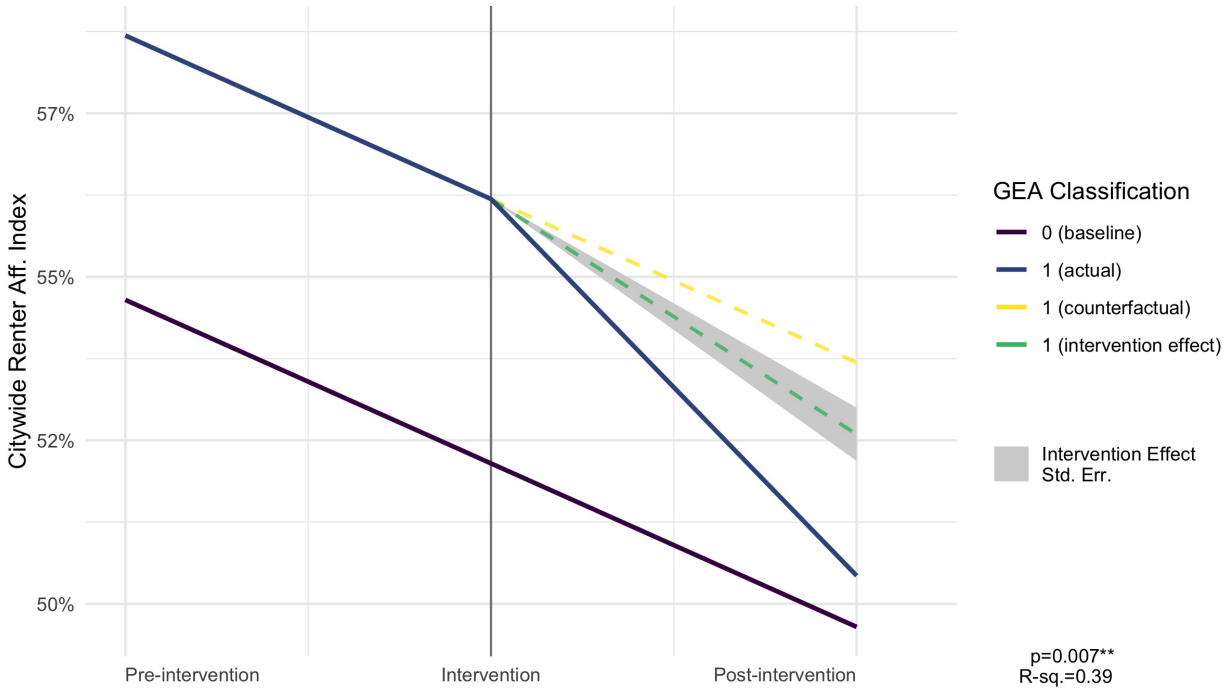


Among the seven outcomes analyzed in this paper, the local renter affordability index returns the weakest conclusions, as shown in figure 6.6. Generally, this index is shown to decrease across both the expanded GEA and non-GEA areas during the study period, a trend which mirrors the citywide average output trends in table 5.1. However, no definitive conclusions can be drawn about the impact of the GEA expansion itself on this trend. The actual decrease of 5.7% within the expanded GEA is closely aligned to both the counterfactual (6.1% decrease) and DiD (5.8% decrease) predictions. The model's standard error of 0.5% is greater than the difference in outcomes, leading to a lack of statistically significant conclusions (p=0.62). While the POLR model concluded with high statistical significance that GEA neighborhoods were slightly more likely to report higher local affordability indicies

than non-GEA ones, the causal order of this relationship cannot be determined by the DiD analysis.

6.3.7 Citywide renter affordability index

Figure 6.7: DiD Impact Analysis: Citywide renter affordability index



Unlike its local counterpart, the citywide renter affordability index produces strong conclusions about the impact of the GEA expansion, as shown in figure 6.7. Within the expanded GEA, this index decreased by an average of 8.3% after the GEA expansion, compared with a decrease of only 5% in non-GEA neighborhoods. About one-third of this 3.3% difference can be explained by the DiD model; the remaining difference is likely attributable to other factors. Overall, these results suggest that the GEA expansion somewhat accelerated the residential exclusivity of affected neighborhoods relative to the baseline, though a sizable portion of this discrepancy was likely attributed to external factors not captured by the

model. These DiD results are in line with the POLR model. Both models support the conclusion that neighborhoods within the GEA are less accessible to prospective renters from across the city than areas outside the GEA, a condition which is largely attributable to the effects of the GEA on housing prices.

6.4 Data and Policy Synthesis

The data analyzed in this paper provide a relatively definitive answer to my first research question regarding citywide trends in neighborhood changes since 2000. Although many of the specific metrics in this paper are unique contributions to the large body of literature around neighborhood change in NYC, the results here are consistent with prior research. From 2000 to 2019, New York grew increasingly unequal based on income, and while housing prices grew rapidly, the supply of housing affordable to low-income New Yorkers failed to keep up with demand. Today, New York is likely a more comfortable place to live for the increasingly large, and increasingly wealthy, segment of the population that is economically well-off. However, low-income residents across the city face a far more hostile environment as their incomes have not kept pace with growing housing costs driven by the wealthier class. The neighborhoods that have long been home to low-income communities are increasingly threatened by gentrification and displacement, and displaced families and individuals have fewer and fewer options for an affordable place to live. Despite these threats, mobility between neighborhoods is lower for New Yorkers today than at most points in the past decade. It remains unclear whether this is a sign of effective anti-displacement municipal policies, or whether it instead points to patterns of gentrification so far advanced that once-contested neighborhoods have become entirely exclusive to low-income residents. Racial integration has improved marginally; however, this improvement has taken place more slowly than in many places across the country, perhaps undermined in part by municipal housing policies that entrench segregation in communities of color.

Given that this analysis supports conclusions from similar prior research, the final ques-

tion of this study becomes more significant: to what extent were the aforementioned trends impacted in affected communities by the expansion of the 421a GEA? It has been established by the POLR model that, all other characteristics held constant, inclusion within the GEA categorically correlates with higher income inequality, improved racial integration, lower rental affordability for all New Yorkers, slightly higher rental affordability for locals, lower social exclusivity, and a higher percentage of residents that are newcomers each year. With the exception of local rent affordability, these metrics are all directionally in line with citywide trends, indicating that inclusion within the GEA exaggerates the degree of neighborhood changes experienced by non-GEA neighborhoods without changing the direction. The DiD model provides an opportunity to evaluate whether this conclusion from the POLR model is indicative of a correlational or causal relationship. Here, the conclusions can be easily grouped by categorizing the outcomes in question:

- **Income inequality:** Both variables related to income inequality (Gini coefficient and 80/20 ratio) returned strong and consistent results throughout. The DiD model indicates that not only did tracts within the expanded GEA see the income gap grow at a higher rate than expected, but the effects of the GEA expansion are highly responsible for these changes. The DiD and POLR models are aligned with each other and with prior research on similar neoliberal housing policies. Given the strength of these conclusions from both an empirical and theoretical perspective, this analysis strongly concludes that the effects of the affordability requirements imposed by the GEA directly lead to higher rates of income inequality when all other variables are held constant.

- **Housing affordability:** The results here are slightly more opaque. Based on the DiD model, local renter affordability does not have a clear relationship with the GEA expansion. The POLR model suggests a clear relationship, but on a very minor scale. On the other hand, the citywide index is empirically higher within the GEA, and the DiD expansion is responsible for at least some of this difference. Once again, literature

on similar neoliberal policies such as inclusionary housing suggests that such programs can accelerate the growth of housing costs. Overall, the GEA can be confidently held responsible for a moderate decrease in a neighborhood's financial accessibility to renters from across New York, although it is not clear whether local renters are also subject to this increased unaffordability.

- **Neighborhood change:** Both variables here (change score and newcomers percentage) are intended to capture year-to-year residential turnover as a proxy for displacement. The hypothesis was that, although neighborhood change has generally decreased in NYC over the past decade, this would not be the case in the expanded portion of the GEA, which has gentrified at a higher rate. However, the statistical models do not support a definitive conclusion to be drawn about this theory. The percentage of newcomers is empirically higher within the expanded GEA than elsewhere, but the model suggests this condition is created in spite of the 421a program rather than because of it. By contrast, change score decreased somewhat more in the GEA than elsewhere, but the DiD model is unable to identify any statistically significant causal relationship. As a result, I do not draw any conclusions about the impact of the GEA on neighborhood change and displacement.

- **Racial segregation:** Finally, the Entropy index model returns similarly inconclusive results. Tracts within the GEA demonstrated significantly higher levels of racial integration than those outside of it, but the direction and degree of any causal relationship are unclear. Prior analyses of housing programs such as inclusionary housing have found correlations in some places with increased segregation rather than integration. In the case of 421a, this relationship can be neither verified nor rejected.

Overall, this analysis concludes that the affordability requirements imposed by the GEA directly exacerbate growing income inequality in affected neighborhoods and makes those areas more exclusive to low-income renters from other parts of the city. However, it is

not clear how this policy impacts racial segregation or neighborhood change, nor can it be determined whether the decrease in overall housing affordability leads to the exclusion of local renters.

6.5 Implications

At a local policy level, the conclusions from this study are highly relevant to the ongoing debate about whether to reinstate some version of 421a and, if so, what alterations to make to the policy. The rebranding of 421a as the Affordable Housing New York program was an intentional decision to market the program as an affordable housing initiative above all else. Gov. Hochul's proposed replacement for AHNY is similarly titled the Affordable Neighborhoods for New Yorkers program, continuing the program's symbolic commitment to advancing affordable housing in New York City. However, opponents continue to criticize the program under all of its aliases as an inefficient policy that largely subsidizes wealthy developments. In the context of neighborhood change, this paper strongly suggests that the 421a/AHNY/ANNY program should be substantially altered prior to renewal in order to mitigate its potential contributions to ongoing gentrification and displacement in NYC. Despite its potential to provide much-needed affordable housing units, the program plays a significant role in creating neighborhoods that are defined by extreme inequality and exclusionary housing costs. An effective version of this program must take steps to mitigate such impacts.

While specific recommendations are outside the scope of this paper, the conclusions here may contribute to a range of policy discussions. New York has extensively explored strategies for increasing the equity and effectiveness of its housing policies. In recent years, mechanisms like community preference and right to counsel have been introduced or expanded in the City's programs. These efforts are intended to make programs like 421a as accessible and beneficial as possible to even the most vulnerable New Yorkers, and their potential for creating opportunities for these households is immense. At the same time, the lack of recent

improvement in many of the trends that have troubled New York for more than two decades suggests that even these innovative approaches have not yet done enough to bring access to affordable housing to those that need it most. These and other ways of improving programs like 421a should be extensively explored and regularly evaluated once implemented.

From an academic perspective, this paper is another installment in the large body of literature that engages with the theoretical approach to strong affordable housing policy. The conclusions outlined here reinforce prior studies that conclude that neoliberal affordable housing policies have negative impacts on neighborhood indicators such as income inequality and housing affordability. However, other conclusions from prior research cannot be replicated in this context, including those that link affordable housing policies with increased racial segregation (Ramakrishnan, Treskon, and Greene 2019a). As outlined in chapter 4, housing advocates and planners frequently criticize the neoliberal suite of housing policy as an inefficient and ineffective apparatus that ultimately contributes to the hyper-commodification of housing in cities. The conclusions established here support these criticisms in the context of the 421a program by demonstrating its negative impacts on equity and accessibility in New York City. While the program has managed to avoid explicitly harming outcomes like neighborhood change and racial segregation, its clear contributions to the extreme economic discrepancies that have come to define New York in the past two decades cannot be ignored.

6.6 Limitations

As with any research paper, even the strongest of conclusions from this analysis should be interpreted with caution in the context of the limitations of the study. A few of the most notable shortcomings are discussed here.

Data Limitations

While the data in this study are gathered from reputable sources such as the U.S. Census Bureau and various New York City agencies, the accuracy of the data is subject to scrutiny.

Because data was collected at the Census tract level, questions of polling accuracy are prescient. The American Community Survey, which is the source for most of the demographic data between 2009 and 2019, cautions against the use of tract-level data for numerical population estimates. While many tracts and variables are likely accurate, some may not be. Likewise, the Comprehensive Housing Affordability Strategy (CHAS) data produced by the Census Bureau and HUD is highly vulnerable to inaccuracies at the tract level given the highly specific cross-tabulation used in this dataset. For example, as many as 50% of tracts in NYC had a margin of error that was as large or larger than the population estimate for CHAS data from the year 2000. While it was necessary to use tract-level data to match the hyper-local scale of the GEA boundary expansion, the limitations of such a small-scale analysis using population estimates creates opportunities for inaccuracy.

On the note of data, I must also note that the output variables used here may contain some internal year-to-year inconsistency. For example, the Census Bureau did not begin disclosing the Gini coefficient or 80/20 ratio until 2010; the values for 2000 and 2009 used in this paper were manually calculated, but may use different underlying data and assumptions than the estimates provided by the Census Bureau from 2010 onwards. Conclusions about the change score in particular are also potentially inaccurate, as no data for 2000 is available for this indicator and there is therefore only one datapoint (2009) from before the GEA expansion.

Spatial Accuracy

As mentioned in the Methodology chapter, the boundaries used to represent the GEA expansion are approximations of the actual boundary used by HPD. The true boundary is drawn at a block-by-block scale; in many instances, individual lots are included or excluded, as are adjacent streets and neighborhoods. The approximation in this study is my attempt to include tracts that included substantial amounts of the GEA. However, there are many tracts included in this approximation that include areas that were not actually within the GEA,

as well as tracts that are not marked as being in the GEA despite containing lots that were included in reality. Although any inaccuracies in aggregated data are likely insignificant, it is possible that such discrepancies do exist.

Temporal Accuracy

Diligent readers may have noticed that the GEA expansion was implemented at the end of 2008, yet I use 2009 data to approximate pre-expansion trends. This is an unfortunate necessity caused by data availability: the American Community Survey, which provides the demographic data used for most independent and dependent variables, did not begin releasing data at the Census tract level until 2009. As a result, I was forced to include 2009 in the pre-expansion dataset in order to have a valid point of comparison for post-expansion data.

On a related note, the pre-expansion dataset includes only 2000 and 2009 - but nothing in between. As a result, pre-expansion trends are approximated using these years as a start and end point, which assumes that data followed a linear trajectory between those two years. This was again necessitated by the data limitations mentioned above, but of course may not be accurate to the ways in which populations shifted between 2000 and 2009.

Internal Validity Concerns

In addition to the above limitations, this study is subject to a variety of internal validity concerns related to both the data and the statistical models. Each output variable is intended to approximate a real-world characteristic, but may not do so with a high degree of accuracy. For example, the Change score is calculated only considering white and Black populations, college-educated residents, and median household income; neighborhood change in reality is a far more complex process that includes many other identities and factors.

The DiD model is a quasi-experimental model, which are often considered to be strong indicators of causal relationships in the social sciences. However, these models are not

flawless. Campbell (1969) famously outlines a variety of internal validity concerns across quasi-experimental methods, each of which may be relevant here. In addition to these general concerns, the DiD model is specifically vulnerable to its own concerns. Most prominently, some have argued that the parallel trends assumption is effectively impossible to prove and thereby undermines the reliability of this model (Rambachan and Roth 2021). Finally, the DiD approach uses the assumption that the only difference between the treatment and control groups is the policy intervention in question, in this case the GEA expansion. Of course, a great many other policies, social movements, political shifts, and other changes happened in New York City between 2009 and 2016 that may have impacted the subjects analyzed in this paper and therefore undermined the internal validity of the DiD model.

External Validity Concerns

External validity concerns exist about the applicability of these conclusions to real-world conditions. Again, Campbell (1969)'s notes on external validity concerns with quasi-experimental methods are relevant. Additionally, these conclusions may not be relevant in New York today for a variety of reasons. The COVID-19 pandemic deeply impacted all of the issues in this paper, from housing development and affordability to residential and employment patterns. These disruptions may have altered post-pandemic conditions such that this study is no longer relevant. This paper also analyzes only the approximately 25% of tracts in NYC that were included in the GEA expansion; however, it is not certain that other neighborhoods would respond in similar ways if subjected to the effects of the GEA.

The results described in this paper also may or may not be relevant to other affordable housing policies in New York City and across the country, even those that may appear similar in nature. Differences in policy nuances, population characteristics, temporal shifts, and geographic variations may lead to an entirely different set of outcomes for a similar analysis of another policy or place.

Qualifying Quantitative Results

Finally, it is worth pausing to consider the definition of desirable and undesirable outcomes as measured by the seven metrics considered in this study. In my discussion, I assign categorical qualifications to changes in direction for each outcome. For example, a higher percentage of newcomers in a neighborhood is seen as a sign of displacement and is therefore considered undesirable, while a higher Entropy index suggests increased racial integration and is therefore classified as desirable. However, the true significance of changes in these metrics in one direction or another may not be so cut-and-dry. If a wealthy white neighborhood that has historically excluded low-income residents and people of color starts to attract such residents, its newcomer percentage increases; this paper may miss this nuance and categorize the change as a negative one, despite the fact that many advocates would agree that making those kinds of neighborhoods more inclusive is a positive change. Likewise, a majority-minority neighborhood that begins to gentrify and therefore attracts more white residents will have a higher Entropy index; most existing residents of that neighborhood would surely call the influx of white neighbors a negative harbinger of gentrification, but this paper might naively classify the change as a step in the right direction. Overall, the qualitative assumptions made about the outcomes in this paper are based in research and are in line with prevailing opinions in the planning field. Nevertheless, data does not tell the whole story, and what may appear as a good or a bad change in this kind of paper may not align with the nuanced conditions in the real world.

6.7 Future Research

While this paper establishes important conclusions about the impacts of 421a in New York, future work is needed to fill existing research gaps. Several key areas for future research are considered below:

- *New inputs and outcomes:* While this study analyzes more than 20 input variables and

7 outcomes, there are many other factors that may be of interest. For example, data related to building and permitting trends, zoning amendments, and other changes to the built environment are highly correlated with this policy, but were not within the scope of this paper. Future research should extend the models used here to consider other such variables of interest.

- *Updated analyses with recent data:* As of this writing, five years have passed since AHNY replaced the original 421a program. Within a few years, there will be sufficient data to analyze the effects of this policy update in a similar manner to the GEA expansion analysis conducted here. AHNY's implementation presents a similar opportunity for a case study, as another set of tracts in NYC were subject to the affordability requirements formerly used in the GEA. A future study to replicate this paper with a focus on the 2017 AHNY implementation would be a valuable way to verify, challenge, or complicate the results found here.

- *Policy recommendations:* Several policy implications and critiques are considered within this paper. However, specific recommendations for how to improve or replace 421a are outside the scope here. New York City has many skilled policy experts dedicated to bringing affordable housing to New Yorkers that need it. Further work must be conducted to apply the results of this paper to actionable program and policy recommendations that can meet this goal and reverse the negative impacts of 421a.

Conclusion

As one of the most prominent and well-funded municipal housing programs in the country, 421a is frequently cited by both opponents and proponents of this approach to housing policy. Proponents, including city and state officials, frequently point to the large number of housing units created by 421a as a vindication of its effectiveness. However, the theoretical context of the hyper-commodification of housing begs a deeper analysis of the program. Whether or not 421a creates affordable housing units is not the only metric that defines the program's success; its impacts on neighborhood outcomes are just as significant, if not more so. Many in the extensive history of affordable housing policies that have preceded and competed with 421a have been shown to harm neighborhoods by exacerbating housing commodification. While proponents of 421a continue to advocate for its ability to break this troubling mold, this paper concludes that the program in fact actively fosters inequality and inaccessibility in neighborhoods across New York City. An affordable housing program that delivers affordable units with one hand while creating more inequitable and exclusive neighborhoods with the other is not one that makes New York a more welcoming place to live for the low-income residents that need such affordability protections. Further entrenching housing and all of its components as a commodity will only lead to greater inequity and greater need in the future. Given its impacts on these outcomes, it appears that 421a is not solving the affordability crisis in New York; it is kicking the can of systemic change down the road at the expense of today's generation of low-income folks that are left behind by the market.

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———. 2010-2019d. (American Community Survey, 5-year Estimates: Table B06009: Place of Birth by Educational Attainment in the United States [Dataset]).

———. 2010-2019e. (American Community Survey, 5-year Estimates: Table B06012: Place of Birth by Poverty Status in the Past 12 Months in the United States [Dataset]).

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Appendix A: Data Dictionary

Classifications

- **geoid2010:** The 11-digit code for each 2010 Census tract containing the state, county, and tract FIPS digits. Data from 2000 and 2009, which originally used 2000 tract boundaries, were converted to 2010 boundaries using U.S. Census Bureau (2010 Census Tract Relationship Files).
  - 2000-2009: TIGER/Line (U.S. Census Bureau, TIGER/Line Shapefiles: Census Tracts, 2000 Boundaries, New York)
  - 2010-2019: TIGER/Line (U.S. Census Bureau, TIGER/Line Shapefiles: Census Tracts, 2010 Boundaries, New York)
- **boro:** The name of the NYC borough in which each tract is located, determined by the tract's county identifier.
  - 2000-2009: TIGER/Line (U.S. Census Bureau, TIGER/Line Shapefiles: Counties, 2000 Boundaries, New York)
  - 2010-2019: TIGER/Line (U.S. Census Bureau, TIGER/Line Shapefiles: Counties, 2010 Boundaries, New York)
- **gea:** Dummy variable classifying each tract by its GEA inclusion. Possible values include 0 (outside GEA), 1 (included in GEA expansion), and 2 (part of original 1985 GEA). Classifications were approximated based on a proprietary GEA boundaries dataset provided by the NY Municipal Arts Society (Municipal Art Society of New York, GEA Approximate Borders).

- **year:** The year for which data was collected for each observation (2000, 2009-2019).
- **time:** A dummy variable used in the DiD analysis to categorize each observation by its temporal relationship to the 2009 GEA expansion. Data from 2000 and 2009 is classified as 0, data from 2010 to 2016 is classified as 1, and data from 2017 and later is classified as 2.
- **did:** A dummy variable used in the DiD analysis to track the time-treatment interaction of each tract. Calculated by multiplying *gea* by *time*. Tract observations within the expanded GEA (gea = 1) and from 2010-2016 (time = 1) are classified as 1; all other observations are classified as 0.
- **geometry:** Spatial data containing the boundaries of each 2010 Census tract.
  - 2000-2009: TIGER/Line (U.S. Census Bureau, TIGER/Line Shapefiles: Census Tracts, 2000 Boundaries, New York)
  - 2010-2019: TIGER/Line (U.S. Census Bureau, TIGER/Line Shapefiles: Census Tracts, 2010 Boundaries, New York)

Independent Variables

- **total_pop:** The total population of each tract.
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 1: Table P001: Total Population)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B01003: Total Population)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B01003: Total Population)
- **total_hh:** The total number of households in each tract.

  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 1: Table H013: Household Size)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B11001: Household Type (Including Living Alone))
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B08202: Household Size by Number of Workers in Household)

- **white_pop:** The total white population in each tract.
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 1: Table P003: Race)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B03002: Hispanic or Latino by Race)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B03002: Hispanic or Latino Origin by Race)

- **black_pop:** The total Black/African American population in each tract.
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 1: Table P003: Race)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B03002: Hispanic or Latino by Race)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B03002: Hispanic or Latino Origin by Race)

- **api_hh:** The total Asian and Pacific Islander population in each tract. This includes residents classified by the Census Bureau as *Asian alone* or *Native Hawaiian and Other Pacific Islander alone*.

  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 1: Table P003: Race)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B03002: Hispanic or Latino by Race)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B03002: Hispanic or Latino Origin by Race)

- **other_pop:** The total population of other racial groups in each tract. This includes residents classified by the Census Bureau as *American Indian and Alaska Native alone*, *Some other race alone*, and *Two or more races*. These groups are combined in this analysis due to small populations and high margins of error in many tracts.
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 1: Table P003: Race)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B03002: Hispanic or Latino by Race)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B03002: Hispanic or Latino Origin by Race)

- **latinx_pop:** The total population that identifies as Hispanic/Latino in each tract. This figure includes residents of all racial groups and is not mutually exclusive with any of the aforementioned race classifications.
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 1: Table P004: Hispanic or Latino, and Not Hispanic or Latino by Race)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B03002: Hispanic or Latino by Race)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B03002: Hispanic or Latino Origin by Race)

- **med_hh_inc:** The median household income of each tract in 2020 U.S. dollars. Data from 2000 and 2009 was converted to 2020 dollars for equal year-to-year comparison.
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 3: Table P056: Median Household Income in 1999 (Dollars) by Age of Householder)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B19013: Median Household Income)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B19013: Median Household Income in the Past 12 Months (In 2020 Inflation-Adjusted Dollars))
- **u_pov:** The number of residents in each tract that live in households with a total annual income that is below the federal poverty line.
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 3: Table P087: Poverty Status in 1999 by Age)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B06012: Place of Birth by Poverty Status in the Past 12 Months in the United States)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B06012: Place of Birth by Poverty Status in the Past 12 Months in the United States)
- **u_pov150:** The number of residents in each tract that live in households with a total annual income that is between 100% and 150% of the federal poverty line.
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 3: Table P087: Poverty Status in 1999 by Age)

  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B06012: Place of Birth by Poverty Status in the Past 12 Months in the United States)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B06012: Place of Birth by Poverty Status in the Past 12 Months in the United States)

- **not_rb:** The number of renters in each tract that are not rent burdened (ie. rent costs less than 30% of household income).
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 3: Table H069: Gross Rent as a Percentage of Household Income in 1999)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B25070: Gross Rent as a Percentage of Household Income)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B25070: Gross Rent as a Percentage of Household Income in the Past 12 Months)

- **rb_mod:** The number of renters in each tract that are moderately rent burdened (ie. rent costs at least 30%, but less than 50%, of household income).
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 3: Table H069: Gross Rent as a Percentage of Household Income in 1999)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B25070: Gross Rent as a Percentage of Household Income)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B25070: Gross Rent as a Percentage of Household

Income in the Past 12 Months)

- **rb_sev:** The number of renters in each tract that are severely rent burdened (ie. rent costs at least 50% of household income).
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 3: Table H069: Gross Rent as a Percentage of Household Income in 1999)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B25070: Gross Rent as a Percentage of Household Income)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B25070: Gross Rent as a Percentage of Household Income in the Past 12 Months)
- **pop_u18:** The number of residents in each tract that are below 18 years of age.
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 1: Table PCT017: Group Quarters Population by Sex by Age by Group Quarters Type)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B05003: Sex by Age by Nativity and Citizenship Status)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B06001: Place of Birth by Age in the United States)
- **pop_18.34:** The number of residents in each tract that are between 18 and 34 years of age (inclusive).
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 1: Table PCT017: Group Quarters Population by Sex by Age by Group Quarters Type)

  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B21001: Sex by Age by Veteran Status for the Civilian Population 18 Years and Over)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B06001: Place of Birth by Age in the United States)

- **pop_35.64:** The number of residents in each tract that are between 35 and 64 years of age (inclusive).
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 1: Table PCT017: Group Quarters Population by Sex by Age by Group Quarters Type)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B21001: Sex by Age by Veteran Status for the Civilian Population 18 Years and Over)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B06001: Place of Birth by Age in the United States)

- **pop_65plus:** The number of residents in each tract that are 65 years of age or older.
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 1: Table P012: Sex by Age)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B16004: Age by Language Spoken at Home by Ability to Speak English for the Population 5+ Yrs)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B06001: Place of Birth by Age in the United

States)

- **hs_or_less:** The number of residents in each tract that have obtained no greater than a high school diploma. This includes residents with high school diplomas and GEDs as well as those that did not complete high school.
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 3: Table P037: Sex by Educational Attainment for the Population 25 Years and Over)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table Sex by Educational Attainment for the Population 25 Years and Over)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B06009: Place of Birth by Educational Attainment in the United States)
- **college:** The number of residents in each tract that have completed some college, regardless of whether a degree was obtained. This includes residents that attended college without obtaining a degree as well as those that obtained associates, bachelors, masters, technical and professional, and doctorate degrees.
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 3: Table P037: Sex by Educational Attainment for the Population 25 Years and Over)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table Sex by Educational Attainment for the Population 25 Years and Over)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community

Survey, 5-year Estimates: Table B06009: Place of Birth by Educational Attainment in the United States)

- **local:** The number of residents in each tract who lived in the same residence one year ago. *Note: The 2000 Decennial Census only provides mobility data from 1995; this number is therefore one-fifth of the provided figure, assuming that year-to-year mobility is equal.)*
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 3: Table P024: Residence in 1995 for the Population 5 Years and Over - State and County Level)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B07003: Geographical Mobility in the Past Year by Sex for Current Residence in the U.S.)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B07010: Geographical Mobility in the Past Year by Individual Income in the Past 12 Months (In 2020 Inflation-Adjusted Dollars) for Current Residence in the United States)
- **migrant:** The number of residents in each tract who lived in a different residence one year ago. *Note: The 2000 Decennial Census only provides mobility data from 1995; this number is therefore one-fifth of the provided figure, assuming that year-to-year mobility is equal.*
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 3: Table P024: Residence in 1995 for the Population 5 Years and Over - State and County Level)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B07003: Geographical Mobility in the Past Year by Sex

for Current Residence in the U.S.)

  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B07010: Geographical Mobility in the Past Year by Individual Income in the Past 12 Months (In 2020 Inflation-Adjusted Dollars) for Current Residence in the United States)

Output Variables

- **gini:** The Gini coefficient of income inequality for each tract. This figure ranges from 0 to 1 and can be interpreted as the percentage of income that would need to be redistributed to achieve perfect income equality. *Note: The Gini index is provided by the American Community Survey starting in 2010. However, the 2000 Decennial Census and 2009 ACS do not provide this data. For these years, the Gini figure was manually estimated using income distribution data.*

  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 3: Table P052: Household Income in 1999)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B19001: Household Income)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B19083: Gini Index of Income Inequality)

- **ratio_8020:** The 80/20 ratio, or the ratio of the 20th income percentile to the 80th percentile in each tract. This figure has no upper bound and higher values indicate a greater degree of income inequality. *Note: Income quintile limits are provided by the American Community Survey starting in 2010. However, the 2000 Decennial Census and 2009 ACS do not provide this data. For these years, these thresholds were manually estimated using income distribution data.*

  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 3: Table P052: Household Income in 1999)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B19001: Household Income)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B19080: Household Income Quintile Upper Limits)

- **chng_score:** The neighborhood change score for each tract, as proposed by Collins (2015). This value is an approximation of a tract's social exclusivity in each year relative to the previous year, with a higher value indicating that the tract became more socially exclusive. See chapter 3 for a precise methodology.
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 1: Table P003: Race; Decennial Census Summary File 3: Table P037: Sex by Educational Attainment for the Population 25 Years and Over; Decennial Census Summary File 3: Table P056: Median Household Income in 1999 (Dollars) by Age of Householder)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B03002: Hispanic or Latino by Race; American Community Survey, 5-year Estimates: Table Sex by Educational Attainment for the Population 25 Years and Over; American Community Survey, 5-year Estimates: Table B19013: Median Household Income)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B03002: Hispanic or Latino Origin by Race; American Community Survey, 5-year Estimates: Table B06009: Place of Birth by Educational Attainment in the United States; American Community Survey, 5-year Estimates: Table B19013: Median Household Income in the Past 12 Months

(In 2020 Inflation-Adjusted Dollars))

- **newcomers:** The percentage of residents in each tract that did moved within the previous year. This figure is an approximation of year-to-year residential turnover, with a higher value indicating greater residential instability.
  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 3: Table P024: Residence in 1995 for the Population 5 Years and Over - State and County Level)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B07003: Geographical Mobility in the Past Year by Sex for Current Residence in the U.S.)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B07010: Geographical Mobility in the Past Year by Individual Income in the Past 12 Months (In 2020 Inflation-Adjusted Dollars) for Current Residence in the United States)
- **rntafflcl:** The local rental affordability index, or the probability that a renter in a given tract can find an affordable rental housing unit within the same tract, based on a similar metric for homeowners proposed by Goodman, Li, and Zhu (2018). This figure ranges from 0 to 1, with higher values indicating a greater degree of housing affordability for local residents. See chapter 3 for a precise methodology.
  - 2000: CHAS (HUD, Comprehensive Housing Affordability Strategy: Table B4; Comprehensive Housing Affordability Strategy: Table B6)
  - 2009-2018: CHAS (HUD, Comprehensive Housing Affordability Strategy: Table 15C; Comprehensive Housing Affordability Strategy: Table 17B)
- **rntaffcty:** The citywide rental affordability index, or the probability that a renter living anywhere in New York City can find an affordable rental housing unit within a

given tract, also based on a similar metric for homeowners proposed by Goodman, Li, and Zhu (2018). This figure ranges from 0 to 1, with higher values indicating a greater degree of housing accessibility to outsiders. See chapter 3 for a precise methodology.

  - 2000: CHAS (HUD, Comprehensive Housing Affordability Strategy: Table B4; Comprehensive Housing Affordability Strategy: Table B6)
  - 2009-2018: CHAS (HUD, Comprehensive Housing Affordability Strategy: Table 15C; Comprehensive Housing Affordability Strategy: Table 17B)

- **entropy:** Theil's Entropy index for racial integration in each tract. This figure is a log-based estimate of the probability that residents within a given tract will experience day-to-day incidental interactions with members of other racial groups. A higher value indicates greater racial integration. See chapter 3 for a precise methodology.

  - 2000: Decennial Census (U.S. Census Bureau, Decennial Census Summary File 1: Table P003: Race; Decennial Census Summary File 1: Table P004: Hispanic or Latino, and Not Hispanic or Latino by Race)
  - 2009: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B03002: Hispanic or Latino by Race)
  - 2010-2019: ACS 5-year estimates (U.S. Census Bureau, American Community Survey, 5-year Estimates: Table B03002: Hispanic or Latino Origin by Race)