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ISBN

9798193222927

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Cabello, Maxwell

Publication Date

2026-10-02

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UNIVERSITY OF CALIFORNIA,
IRVINE

Sources of Variation in Affordability Amongst Market-Rate Housing Units
in the United States, 2015 to 2023

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Urban and Environmental Planning and Policy

by

Maxwell Brooks Cabello

Dissertation Committee:
Associate Professor Nicholas Marantz, Chair
Professor Jae Kim
Professor Matthew Freedman

2026

DEDICATION

To

My family for being my consistent refuge of peace and never mistaking my focus for absence. And especially to my wife, who brought our second child into the world during my third year, and our two children who brought laughter, joy, and chaos into nearly every day I worked on this project.

And my parents, whose own material struggles were followed by generosity that ultimately shaped both who I am and what I want to accomplish. I hope this a small part in living up to your example and continuing your legacy of showing care and empathy for those who are often forgotten or ignored.

To my friend, and oftentimes mentor, Youjin, who filled the gaps when I was unsure of how to maintain progress or take the next step in this process and always found the right words of encouragement at critical times in this process. To my other friends and family who filled my free time with adventure, fun, laughter, and reprieve when I most needed it.

And my union and fellow graduate students who collectively ensured we had access to healthcare, funding for childcare, paternity leave, and the support needed to finish this project.

To all the folks who are “doing the work” and are in the trenches demanding a better world. I hope this project brings to light what is known on the ground—that finding safe, dignified, and affordable housing can be uniquely difficult to those who already face intersecting forms of oppression. Those who occupy and organize in this space understand that many other uses of one’s labor, effort and focus would likely yield more favorable material rewards; but continue to fight even in trying times like those we find ourselves in now. Thus, I am reminded of the great scholar-activist Walter Rodney’s courageous words that preceded his assassination in Guyana:

“It is imperative that I stay here”

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ACKNOWLEDGMENTS

Thank you to my advisor and committee chair, Professor Nicholas Marantz, whose steady hand and guidance consistently helped me maintain progress and focus. His feedback was always thoughtful, challenging, and immensely helpful in shaping my vaguely formed ideas into fully formed ideas and areas of inquiry. I would also like to thank my other committee members, Professor Jae Kim and Professor Matthew Freedman, who provided helpful feedback and guidance as I developed my proposal, especially by pointing me towards helpful literature and measures that ultimately shaped many portions of this project.

Many of the regression outputs and tables were derived from the Internal Use File (IUF) of the American Housing Survey (AHS), which required accessing the IUF at the UC Irvine Federal Statistical Research Data Center (FSRDC). These are appropriately identified via the project number (3221) and request numbers (R13043 and R12982). I want to acknowledge the support provided from the Census Bureau and UCI RDC administrators, in particular by Matthew Freedman, Kamal Bookwala, and Bryce Hannibal who helped me prepare my proposal, attain approval, and navigate my time at the RDC.

Any views expressed are those of the author and not those of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3221. (CBDRB-FY26-P3221-R13043 & CBDRB-FY26-P3221-R12982)

UC Irvine's Graduate Division partially funded this work via the Graduate Dean's Dissertation Fellowship award during the Summer of 2025. This funding was utilized, at the researcher's sole discretion, to cover the FSRDC's data access fees and also supported the purchase of other supplemental data used as part of this project.

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Housing Policy and Planning

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Cabello, M., Hyland, M., & Marantz, N. (2023). From state of the practice to state of the art: Improving equity analysis in regional transportation plans. *Transportation*.
<https://doi.org/10.1007/s11116-023-10439-4>

Kim, J. H., Barajas, J. M., Marantz, N. J., Houston, D., Herrera, V., Okashita, A., & Cabello, M. B. (2024). Assessing the Potential for Densification and VMT Reduction in Areas Without Rail Transit Access. <https://doi.org/10.7922/G22V2DGJ>

Reyes, A., & Cabello, M. (2025). Contention and change in Southern California: Post-suburban governance and its evolution. *Journal of Urban Affairs*, 1–23.
<https://doi.org/10.1080/07352166.2025.2470769>

ABSTRACT OF THE DISSERTATION

How Affordability Shifts Vary Amongst Market-Rate Housing Units
in the United States, 2015 to 2023

by

Maxwell Brooks Cabello

Doctor of Philosophy in Urban and Environmental Planning and Policy

University of California, Irvine, 2026

Associate Professor, Nicholas Marantz, Chair

One of the most common approaches to addressing the pervasive housing affordability crisis throughout the U.S. has been to change laws and land use regulations in order to induce increased housing production. Increased production is meant to induce the “filtering” process whereby existing housing units “filter down” to lower income households over time, becoming Naturally Occurring Affordable Housing (NOAH). Some remain skeptical that this process delivers beneficial outcomes to low-income and Black, Indigenous, and People of Color (BIPOC) households in particular. Using a longitudinal panel of housing units from the American Housing Survey (AHS) from 2015 to 2023 along with two measures of affordability, I analyze how affordability amongst market-rate housing units in the U.S. shifts over time and how geographic, housing supply, housing cost trends, and household characteristics relate to filtering dynamics in the U.S. I find that filtering slows amongst units 50 years and older, poorer quality units are more likely to filter downward, and rental units that have been rehabilitated are more likely to filter upward. I also find that owner-occupied units are more sensitive to changes in housing supply while rental units respond more to changes in housing costs. Gentrification’s impacts to affordability are mixed, depending on the affordability measure used, though there is distinct variation in outcomes between neighborhoods that are affluent, low-income, and low-income areas experiencing change. I also find that Black and Hispanic/Latino households face barriers in gaining access to NOAH compared to other households. Lastly, I find that, depending

on the measure used, units identified as affordable may obfuscate the fact that many of their occupants have high housing cost burdens. These outcomes paint a complicated picture—while increased supply does seem to have important implications for housing affordability, downward filtering has generally slowed in the last decade and there is evidence that low-income, BIPOC households have barriers to accessing NOAH in particular.

CHAPTER 1: Introduction

1.1 Statement of Purpose

In recent years, the relationship between housing supply and affordability has become a salient topic of discussion amongst academics, policymakers, and activists. These discussions have meaningfully impacted political narratives and policy proposals, particularly as low-income households continue to struggle to find affordable housing across the country (Getsinger et al., 2017). In New York, activists pressured the legislature to pass expanded renter protections in 2019 while efforts to drastically expand housing production stalled due in part to progressive lawmakers' desire to include just cause eviction protections for renters (Ferré-Sadurní, 2023; Mironova et al., 2022). The California legislature has passed over 100 housing laws since 2017 that are primarily focused on encouraging the expansion of housing supply by reducing barriers to housing construction in various instances and have shown early signs of success (Fulton et al., 2023; Monkkonen et al., 2023b; O'Neill & Wang, 2023). Even the federal government, which typically has little influence on local zoning and land use regulations, has encouraged the removal of local barriers to expanding housing supply and required local governments to analyze housing needs and segregation patterns (Monkkonen et al., 2023a; The White House, 2016). At the city-level, governments and legislators have debated and implemented property tax abatements to incentive higher density housing development, eliminating single-family zoning (e.g., making duplexes or triplexes legal by-right, citywide), transit-oriented development, and other policies to increase housing supply.

There is ample evidence from researchers that increased housing supply generally reduces housing costs and induces the process of “downward filtering”—when a unit becomes more affordable over time (Been et al., 2019, 2023). However, there is relatively little literature on the extent to which supply-side housing policies directly impact low-income and Black,

Indigenous, and other people of color (BIPOC) households over time. The lack of research in this area is one reason skepticism has persisted amongst activists and progressive legislators regarding more aggressive expansion of housing supply in high-cost cities, particularly due to concerns around gentrification and displacement. Many researchers have validated the importance of housing supply to providing more housing opportunities and improving affordability in aggregate, but generally it is more difficult to make assertions on how specific households and groups (e.g., Black or Hispanic households) are impacted by shifts in housing supply. This dissertation aims to provide insights and evidence to inform this component of the debate around housing supply and affordability as race/ethnicity in the context of filtering has yet to be thoroughly evaluated.

This dissertation addresses several research questions but is broadly guided by the aim to quantify the degree to which filtering contributes to the affordable housing stock for both low-income and BIPOC households in the United States. This study exploits an under-utilized dataset that is rich in household-level characteristics and is longitudinal in nature, the American Housing Survey. Other researchers have recently used this dataset to quantify the extent to which unsubsidized, unaffordable housing filters downward over time nationally as well as how it varies by geography (Spader, 2024; Weicher et al., 2017). However, these analyses have stopped short of evaluating how filtering varies across demographic groups and specific housing market types.

This study extends and innovates on these past studies in three ways. One, it evaluates filtering dynamics based on specific housing market characteristics (e.g., changes in housing supply, relative level of land use regulations, etc.) as opposed to broader geographic levels. Second, it looks at how filtering varies by ethno-racial groups. Lastly, it uses and compares two

different measures for affordability to better understand the advantages and limitations of prior measures used by researchers. These innovations allow for deeper engagement with four research questions related to housing policy that inform how this study has been developed. First, how frequently do unsubsidized units filter downward nationally and what are the characteristics of units that do so (age, quality, level of rent burden, etc.)? Second, how does filtering vary by geography and housing market type (e.g., high versus low supply increases)? Third, how does filtering vary by household characteristics (e.g., household income, race/ethnicity, etc.)? Lastly, to what degree (and direction) do household, geographic, and housing market characteristics impact the frequency of filtering?

The remainder of this section provides a brief overview of the policy context that has motivated this dissertation. First, I provide an overview of how recent state- and city-level housing reforms meant to expand housing supply have been rationalized and operationalized, with a focus on California's recent rehaul of state housing law. Additionally, I describe the logic employed by progressive activists who have specific concerns around gentrification and displacement, particularly as they relate to racial equity; of note, while not the focus of this section, a brief overview of how NIMBY homeowners' arguments are distinct from those made by progressive activists is also included here. This chapter closes with a brief overview of remaining chapters.

1.2 Background

This section will describe the current policy environment that, in part, has motivated this research. While Section 2 provides an overview of academic literature that foregrounds this study, it is worthwhile describing how housing policy is currently being discussed and applied in

the United States. As this study aims to inform housing policy discussions and formation, and understanding of its current state is important, particularly the degree to which filtering is being relied upon as a strategy to address housing affordability. While this study evaluates filtering outcomes nationally, there is a specific concern regarding housing markets, predominantly large coastal cities, where affordability—and, often, supply—is most scarce. As such this background section highlights policy discussions and tactics being deployed largely in high-cost coastal cities in the United States.

1.2.1 Recent reforms to expand housing supply

Expanding housing supply has become a common strategy to address housing affordability in cities in the United States. This strategy is rooted in the idea that increases to the housing supply will increase housing choice for households and ultimately induce a process called downward filtering, which involves units depreciating in quality and price as the age, making them more affordable. This process can be induced by the creation of newer, more expensive units, which can initiate a chain of moves that make older, more affordable housing units available (Mast, 2023). Chapter 2 provides an overview on literature related to filtering, but generally speaking policymakers are trying to induce this process by increasing housing supply. California has been aggressively pursuing this strategy by passing housing legislation that largely expands housing supply in recent years, passing over 100 housing laws since 2017 to do so (Fulton et al., 2023).

In places like Los Angeles, municipal-level reforms and voter mandates have led to programs and changes in zoning that expand housing density, reduce parking requirements, and incentivize affordable housing development (Gabbe, 2019). In New York City, both the de Blasio and Bloomberg administrations used neighborhood rezonings to increase housing

production as well as incentivize (or require) affordable housing development through inclusionary zoning mechanisms (Kazis et al., n.d.). Minneapolis and St. Paul both eliminated single-family zoning citywide in response to a regional housing shortage, though Minneapolis is facing a lawsuit over their implementation of this policy (Griswold & Croman, 2023; Liang et al., 2024). The City of Vancouver and State of Oregon have also implemented similar reforms in recent years to address housing shortages (Wegmann, 2020).

While the exact tactics vary by place, in general there are many discussions on how to reduce barriers to housing construction, even at the federal level (White House, 2016). Common approaches include eliminating or reducing parking requirements, expediting permit approvals, narrowing the scope of environmental assessments, providing density bonuses near transit and/or for affordable housing, tax abatements for multifamily housing, and allowing for accessory dwelling units and/or lot splits, and converting non-residential buildings to housing. Governor Newsom in California signed a package of 56 housing bills in October of 2023 with a focus on “expediting the construction of new housing, protecting tenants, and keeping housing affordable” by reforming environmental review processes, expanding enforcement of housing laws, and expanding access to financial resources for affordable housing projects (Office of Governor Gavin Newsom, 2023). The State of California also has specifically developed and allocated financial incentives for localities that are deemed to be “prohousing” (California Department of Housing and Community Development, 2022). While California’s reforms have been far reaching and included increasing enforcement of existing laws, they have been met with local resistance from some charter cities in particular. However, efforts from these cities to subvert or overturn state law has been largely unsuccessful and California cities now face real

consequences if they fail to adequately plan and zone for future housing growth (Reyes & Cabello, 2024).

While Chapter 2 goes into more detail regarding evidence from scholarly research on supply-side housing strategies, my motivation for this research is largely derived from the ubiquity of such strategies in practice. Understanding how such programs and increases to supply impact different groups is critical in shaping and reshaping these types of policy reforms.

1.2.2 Concerns about gentrification and displacement

While supply-side strategies to address housing affordability have gained traction recently, there has also been opposition to this approach. Some of this opposition is derived from NIMBY groups who oppose any changes that change the characteristics of their primarily single-family neighborhoods (Kahlenberg, 2020; Rouse et al., 2021). However, there has also been concern from tenant groups and other stakeholders regarding the possibility of gentrification and displacement derived from increased private development. There are also scholars who have questioned the efficacy of supply-side housing strategies to meaningfully address housing affordability for BIPOC and low-income households, arguing that increased development and housing density do not adequately address the fundamental issues causing housing issues (Curran, 2022; Teresa, 2022).

Importantly, this position has not been merely an intellectual one, but it has resulted in tangible housing policy changes. In 2019, the New York state legislature passed the Housing Stability and Tenant Protection Act (HSTPA), which focused on limiting rent increases in stabilized housing units, including closing several loopholes that allowed larger rent increases in certain circumstances (NYU Furman Center, 2021). At the city level, all rezonings that increase the amount of housing that is allowed to be built are required to include a percentage of affordable housing units per a citywide zoning ordinance passed in 2016 (New York City

Council, n.d.). In 2021 New York City also passed a law that requires developers and other parties who apply to rezone their properties to submit a Racial Equity Report describing how their proposal impacts BIPOC and low-income residents (Fiore, 2023). Due to political pressure from tenant activists and concerns around displacement, New York City's 421-A tax abatement program was allowed to expire despite its decades long existence as a policy tool to encourage housing development. However, after a year of construction slowing down and lobbying from real estate groups, the state legislature enacted a replacement program (David, 2024; Zaveri, 2024).

Similarly, smaller cities and more suburban municipalities are enacting rent control policies in response to rising rents and pressure from local residents (Kramo, 2023; Reyes & Cabello, 2024). Following the economic theory underlying the approaches described in the previous subsection (1.2.1 Recent reforms to expand housing supply), historically (and presently) there are concerns that more restrictive rent control policies will disincentivize construction and supply leading to increased housing prices.

With these two perspectives often being diametrically opposed in forming housing policies to address the looming affordability crisis across cities in the United States, understanding the importance and limitations of supply-side solutions is critically important. While this study does not necessarily focus on outcomes of up-zonings or specifically evaluate supply-side policies or tenant protections, it does thoroughly analyze the process of filtering which is central to this debate in many ways. Thus, this study provides critical analysis of current trends nationally and in certain contexts that might help better inform activists, elected officials, community members and policy makers who want to address the housing affordability issue that impacts households across the United States.

1.3 Key terms, acronyms, and definitions

Below are acronyms and terms that are worth defining up front, as they will be used iteratively throughout this study. I will re-introduce these terms and acronyms when they are first used in the text, but this list can be referred to in case the reader is unfamiliar with a term or acronym used later in this document.

American Community Survey (ACS)¹: this cross-sectional survey is carried out by the U.S. Census Bureau annually on a sample of residents. The survey asks questions about income, housing, demographics, and other characteristics of households. This data is aggregated at various geographic levels, including county, census tract, etc.

American Housing Survey (AHS): this longitudinal survey is the primary source of data in this study. This dataset is a weighted sample of housing units that are representative of housing units at the national level and include characteristics on both the units and the households that occupy them.

Area Median Income (AMI): AMI is an income threshold for a given CBSA/MSA, which is functionally the midpoint of a given region's household income distribution.

Black, Indigenous, and People of Color (BIPOC)²: BIPOC is meant to center the acute structural oppression experienced by Black and Indigenous people in the U.S. particularly when discussing how structural racism impacts a variety of communities today.

Bureau of Labor Statistics (BLS): a part of the U.S. Department of Labor that is the principal fact-finding agency in regards to labor economics and statistics.

¹ The Census Bureau releases 1-year and 5-year surveys (i.e., 1-year of sampled households versus 5-years of sampled households informing estimates); both are released annually, but in this study any ACS dataset can be assumed to be a 5-year sample unless otherwise clarified as it is more reliable than 1-year estimates

² This is an umbrella term that is meant to be inclusive but, like most umbrella terms, is imperfect. I use this term throughout this paper with the intention of acknowledging historically racialized inequities that presently impact numerous communities.

Core-Based Statistical Area (CBSA) and Metropolitan Statistical Area (MSA)³:

CBSAs are inclusive of MSAs and Micropolitan Statistical Areas. Micropolitan areas are smaller (at least 10,000 and less than 50,000) in population than MSAs (50,000 or greater). This study will not evaluate micropolitan areas as it is concerned with larger cities, but CBSA is used simply because that is the geographic variable the AHS uses in their datasets.

Comprehensive Housing Affordability Strategy (CHAS): this dataset is a custom tabulation of ACS data to demonstrate the extent of housing needs and problems to households eligible for HUD funded programs. Importantly, they tabulate ACS data by the HUD Area Median Family Income, which makes it possible to quantify the number of households at various AMI tiers.

Consumer Price Index (CPI): an index released by the BLS that provides year over year consumer inflation estimates based on the change in prices paid by urban consumers for a market basket of goods and services.

Gross rent threshold: This is one of the two measures for filtering that I will use in this study, though the term is my own. Broadly, this measure tracks how gross rent changes over time relative to a given AMI threshold, generally 50% of AMI in the following analyses. For a more detailed description, please refer to *3.3.2 Gross rent threshold*.

HUD (U.S. Department of Housing and Urban Development): the federal housing agency in the U.S. that oversees all federal housing programs and associated funding. They also set Fair Market Rents based on various AMI tiers.

³ A more detailed description can be found here: <https://www.census.gov/programs-surveys/metro-micro/about.html>

Internal Use File (IUF) and Public Use File (PUF): There are two versions of each AHS dataset, a file available for public use (PUF) and an internal file (IUF) with identifying information (e.g., geographic characteristics⁴) that is only available with approval from a Federal Statistical Research Data Center.

Low-Income Housing Tax Credit (LIHTC): The largest federal housing construction program since shortly after its inception in 1986, overtaking public housing construction in quantity almost immediately and accounting for nearly a third of all multi-family construction from 1987-2006. This program funds development of affordable housing via tax credits that are typically sold by developers to investors in order to fund their projects.

Naturally Occurring Affordable Housing (NOAH): This term refers to privately-owned housing that is affordable to lower income households without the tenant or unit receiving subsidies (e.g., voucher holders, public housing units, etc.).

Repeat Income Model: This measure quantifies changes in income level when the households that occupy a unit turnover from one household to a new one. This measure is replicated from prior researchers and quantifies how much more affordable a unit becomes over time based on the household income of the unit's occupant. For a detailed description of this measure, please refer to *3.3.1 Repeat Income*.

Rent burden: Throughout this document, the definition for rent burden (or rent burdened households) will follow HUD's definition. HUD defines rent burdened households as those who pay more than 30% of their gross household income on rent. **Severely rent burdened households** are those who pay more than 50% of their gross income on rent.

⁴ The PUF data does not make available any geographic identifying characteristics below the Census Division level except for observations in CBSAs with published metro data in that year. For example, observations in the New York City CBSA would be identified as being in that CBSA since it is published every survey year.

Wharton Residential Land Use Regulation Index (WRLURI): an index that quantifies the restrictiveness of local land use regulations (Gyourko et al., 2021). This index's interquartile range runs from -0.68 (25th percentile) to 0.62 (75th percentile) and a standard deviation of 1 by design. A higher WRLURI value indicates that a jurisdiction is more highly regulated.

1.4 Summary and overview

This study was developed in response to important and salient policy debates active amongst policymakers, legislators, activists, homeowners, and numerous other stakeholders in regarding housing affordability. Particularly, these groups are actively engaged in debate about the role of market-rate housing supply in contributing to the affordable housing stock for low-income households. There are also concerns about how structural racism that has persisted in housing outcomes in the United States might be reproduced or reinforced without policies that protect tenants or produce deeply affordable housing. This study aims to provide more context for this debate and to quantify the role of unsubsidized market-rate housing in providing affordable housing to low-income and BIPOC households in particular. Understanding the importance (and limitations) of market-rate housing can better inform policymakers on which housing policy strategies are most appropriate and effective at improving equity.

The remainder of this paper is structured as follows. Chapter 2 provides a review of research quantifying the relationship between housing supply, affordability, and downward filtering. This chapter also reviews literature on the impacts of subsidized housing to low-income and BIPOC households, including how outcomes vary by ethno-racial characteristics of householders. Chapter 3 provides a detailed description of the methodology and data used in the analyses outlined in the remainder of this study. Of particular interest may be *3.3 Filtering*

measures, which provides details on how filtering will be measured in the proposed analyses.

This study will use two different methods, one that measures filtering based on changes to a household's income level (repeat income) and the other measures filtering based on changes to a unit's rent level (gross rent threshold). *3.4 About the AHS* also identifies and describes potential methodological challenges related to using this dataset.

Chapters 4 through 7 provide descriptions of the specific analyses to be done on the AHS data. *Chapter 4* evaluates filtering nationally without tabulating data geographically or by household characteristics. The objective of this chapter is to ascertain how many affordable housing units are lost and produced via the process of filtering nationally during the time frame analyzed. *Chapter 5* evaluates spatial variation of filtering and extends existing research by examining variation of different types of geographies and using new measures to cluster geographies for comparison. *Chapter 6* evaluates filtering variation by household characteristics, perhaps the most novel analysis in this study. This analysis looks at variation by ethno-racial characteristics of householders as well as variation by household income level to better understand how households may be differentially impacted by filtering. *Chapter 7* provides an overview of final conclusions, limitations, policy implications, and areas for future research.

CHAPTER 2: Literature Review

2.1 Relationship between housing supply and affordability

Naturally occurring affordable housing (NOAH), or housing units that are privately owned and unsubsidized but still affordable, is an important source of affordable housing for low-income households in the United States. In fact, Weicher et al. (2017) found that public and assisted housing units were never the predominant source of affordable housing in the United States between 1985 and 2013. Importantly, research has found that negative trends in rental housing affordability can be attributed in part to increased regulations, both quality requirements and local land use regulations, limiting housing production and affordability (Malpezzi & Green, 1996; Quigley & Raphael, 2004; Somerville & Mayer, 2003).

Other researchers have investigated this topic in a variety of forms and geographies, largely affirming the general inverse relationship between the amount of housing regulation and affordability. When regulations and zoning are more restrictive, housing costs are higher while vacant land costs are lower, as Ihlanfeldt (2006) found in his model measuring the effects of increased regulations on Florida cities. As a result, more regulations and strict zoning can reduce new housing production that would otherwise instigate the “filtering down” of existing units to lower income households. The general consensus on this phenomenon has been documented by researchers (Been et al., 2019, 2023) and other effects have also been attributed to lack of housing production, like decreased economic productivity, increased segregation, and upward filtering in tight housing markets.

However, while Glaeser and Ward (2009) found minimum lot size requirements and other regulations reduced housing production, their results had no effect when controlling for demographics and density, finding that affluent areas have more expensive housing markets

regardless of use regulations and that denser areas issue more building permits. Recent research exploring the relationship between supply constraints and home prices found that changes in incomes and labor shifts (i.e., demand) were far more predictive of changes to home prices than supply elasticity or other supply focused measures like WRLURI (Louie et al., 2025). Another important caveat within this body of research is that many scholars point out that some form of income-based subsidy would still be necessary to make private, market-rate housing affordable to the lowest-income households (Been et al., 2019; Malpezzi & Green, 1996).

Overall, the idea that local land use regulations increase housing costs is largely accepted based on the evidence produced by researchers. Essentially, increased housing prices due to regulations limits supply and the resulting lower levels of new housing production slow the filtering process that would produce more “naturally occurring affordable housing” units. While many housing academics continue to put forth and generally accept the idea that more restrictive regulations lead to higher housing costs, this idea is closely related to the impact of downward filtering, which is crucial to producing NOAH.

2.1.1 (Downward) Filtering

Downward filtering is the process of properties aging and depreciating in quality and price, which in turn makes them affordable to lower-income households (Liu et al, 2021). This process has been evaluated in a variety of research and has become a generally accepted theory. Scholars have evaluated the phenomenon specifically as it relates to low-income households and have found that filtering is the primary source for affordable housing in the United States (Weicher et al., 2017) and that housing costs have been trending upward for these households in recent decades. That trend, they claim, is not due to the lack of efficacy of filtering, but rather land use regulations that increase the costs to build new housing that are therefore passed along

to renters (Malpezzi & Green, 1996; Quigley & Raphael, 2004). Other scholars have affirmed filtering as a phenomenon but also pointed out that its effects can be uneven across affordability tiers, with housing stock that is affordable to lower-income tiers being lost in recent years (Collinson, 2011). In general, most housing scholars seem to agree that housing costs are growing more than real wages, which have seen modest gains at best, or even losses, depending on the exact time frame evaluated. While scholars have provided evidence of the theory of filtering based on their research, evaluating its efficacy in addressing very low-income housing needs in specific housing markets has been evaluated less frequently.

Numerous scholars have also evaluated the impacts of market-rate housing on nearby housing prices and rent levels. When evaluating the impacts of large, market-rate developments on high-income census tracts, Mast (2023) found that moves associated with these new market-rate units created a “vacancy chain” that ultimately opened up housing units in lower-income neighborhoods. Mast (2023) estimates that for every 100 new units developed on a high-income tract, 70 units in below-median income tracts and nearly 40 units on low-income tracts can be expected to become available to new tenants based on the anticipated series of moves, though the author notes that in many cities low-income areas actually have much higher vacancy rates so impacts to these areas may vary based on context. Similarly, other researchers have found that rents near new, market-rate developments on low-income tracts are five to seven percent lower than other similar areas (Asquith et al., 2020) and in San Francisco a random selection of new developments were associated with a two percent decrease of nearby rents in addition to a reduced risk of displacement of renters to lower-income tracts (Pennington, 2021).

Other research has both affirmed the phenomenon of filtering and described its differential effects depending on local market conditions. Rosenthal (2014), as well as other

researchers who adopted Rosenthal's research design (Liu et al, 2021; Spader, 2024), have evaluated filtering at regional and metropolitan levels, with interesting results. In areas with higher housing costs and housing price inflation, filtering is less effective in providing affordable housing units. Specifically, in lower cost housing markets (e.g., Chicago and Detroit) and higher cost units within markets, filtering occurs more prominently than in higher cost housing markets (e.g., Los Angeles and Washington DC) and lower cost units within housing markets (Liu et al, 2021; Spader, 2024). They also find that filtering is correlated both with housing prices and the restrictiveness of local land use regulations. Within metropolitan areas, filtering is less prevalent in gentrifying areas, especially those close to city centers, meaning local market conditions may have greater influence over filtering than the characteristics of individual housing units alone (Liu et al, 2021; Somerville & Holmes, 2001). Similarly, while Mast (2023) found evidence of filtering occurring within three years of new developments in the 12 largest cities in the U.S., they also pointed out that census tracts with low-incomes and high-rent burdens already had relatively high vacancy rates, which could indicate that filtering might not decrease rents in these neighborhoods even if it does occur. Importantly, there also is evidence that tracts with more restrictive zoning regulations are more likely to be rental deserts, have more affluent households, and have higher proportions of White households, indicating that a lack of housing supply in affluent areas may be creating barriers to low-income, BIPOC households in particular (Airgood-Obrycki et al., 2026).

The scholarship discussed thus far generally supports the idea that filtering is effective, albeit to varying degrees, at supplying affordable housing. However, it is worth noting that many scholars have been skeptical at filtering's effectiveness in addressing affordable housing needs for low-income households, both in the United States and in other countries (Galster, 1996; Palm

et al., 2020; Skaburskis, 2006; Smith-Heimer, 1990; Turner & Wessel, 2019). Fundamentally, these authors find that many older units are not necessarily filtering over time and largely remain unaffordable to low-income households in the markets they are evaluating. Some scholars have also claimed that in scenarios where filtering theoretically would be most effective in suppressing rents for low-income households, where new construction exceeds household formation, the consequences likely would be degradation of housing quality and neighborhood abandonment that would offset any gains in affordability (Bond & Coulson, 1989; Galster, 1996). Importantly, there is also evidence that higher rent burdens and the concentration of at-risk and affordable units are correlated with inadequacy issues, perhaps indicating that, for some renters, units with inadequacy issues are important sources of housing while also not necessarily relieving their rent burdens (Hipp et al., 2025).

To conclude, scholarship indicates that filtering produces a significant proportion of affordable housing stock in the United States (Liu et al, 2021; Weicher et al, 2017) but occurs at higher rates in cities with lower housing prices. Since filtering is an expression of the housing market, it is sensitive to both supply and demand. Galster (1996) concludes that filtering struggles to provide long-term benefits to low-income households because it requires new construction to outpace household formation in specific sub-markets, which skews towards luxury sub-markets.

2.2 Importance and impacts of subsidized housing to low-income and BIPOC households

Housing subsidies and regulated housing in the United States play a critical role in providing affordable housing to low-income households. At a macro-level, nearly three million renters receive federal assistance to afford adequate housing—around one million receiving

Housing Choice Vouchers (HCV), around 800,000 receiving project-based vouchers, around 650,000 living in public housing, and around 400,000 receiving other forms of housing assistance. The scale of this housing stock pales in comparison to the demand for housing affordable to extremely low-income (ELI) households—those earning less than 30 percent of Area Median Income (AMI)—with only 46 ELI units available per 100 households (Getsinger et al., 2017). Public housing units and HCV generally target lower-income tiers while units in buildings receiving low-income housing tax credits (LIHTC) generally target more moderate-income households. As a result, public housing and HCV have strong effects on affordability for ELI households while LIHTC units only have significant effects on very low-income households—those earning less than 50 percent of AMI (Lens, 2018).

The following two subsections outline the impacts of both (1) direct housing subsidy programs (public housing and HCV) and (2) LIHTC development to ELI and BIPOC households. Given their unique strategies and targeted income levels, an independent evaluation of each of these programs is necessary.

2.2.1 Direct housing subsidies: public housing and housing vouchers

The use of the Rental Assistance Demonstration (RAD) program to rehabilitate public housing has been substantial in magnitude and has led to the conversion of public housing units to private ownership. Funding from RAD easily eclipses capital funds available to PHAs for maintenance and rehabilitation and, to some extent, uses LIHTC credits that would otherwise expand housing production (Schwartz, 2017; Schwartz & McClure, 2021). There is also some evidence that this program may induce gentrification and displacement compared to similar neighborhoods that did not make use of the program (Lowell & Smith, 2022). Overall, subsidized and/or assisted housing units provide more than half of the housing units affordable to

ELI renters, with the remainder being provided by naturally occurring affordable housing (Getsinger et al., 2017).

In addition to providing housing that is affordable to ELI renters, subsidized and regulated housing can also provide increased stability. Researchers have found that while evictions, likely driven by good cause eviction policies, occur less frequently in subsidized property compared to unsubsidized properties, within subsidized properties Black and ELI tenants still experience consistently higher rates of eviction (Harrison et al., 2021; Preston & Reina, 2021). In evaluating New York City's rent-stabilization program, Zapatka and de Castro Galvao (2023) find evidence that foreign-born and non-White Hispanic households were more likely to live in rent-stabilized units than non-Hispanic White and native-born households and that rent-stabilized households saved money initially and over time compared to households in non-stabilized units. They estimate rent savings of over \$18,000 for rent-stabilized tenants from 1991-1996 and of over \$37,000 from 2002-2008. While there is statistical evidence that stabilized tenants realized significant savings, they found those savings do not translate into shifts in rent burden status.

There also is some evidence that voucher holders are overcharged by landlords, with researchers estimating that HCV holders in Milwaukee are charged between \$51 and \$68 more in monthly rent compared to unassisted renters in comparable units, resulting in over \$4 million worth of overcharges in Milwaukee alone (Desmond & Perkins, 2016). There also is evidence that HCV holders have lower location efficiency in terms of accessibility to jobs and transportation modes and that increased travel costs may erode the benefits provided by HCV (Tremoulet et al., 2016). While not directly related to vouchers, it is also important to note that researchers have found that Black households are far more likely to move from nonpoor to poor

neighborhoods compared to White households while also being far more likely than White households to move from a nonpoor to poor neighborhood (Crowder & South, 2005). To a similar end, there has been evidence of homes in Black neighborhoods being significantly devalued (21-23% lower) when compared to similar homes in non-Black neighborhoods as well as evidence that Black and Hispanic households pay a premium for similar homes compared to White, non-Hispanic households (Bayer et al., 2017; Rothwell & Perry, 2022).

2.2.2 Low-Income Housing Tax Credit (LIHTC)

In the United States, the Low-Income Housing Tax Credit (LIHTC) has been the largest source of affordable housing development since shortly after its inception in 1986, overtaking public housing construction in quantity almost immediately and accounting for nearly a third of all multi-family construction from 1987-2006 (Eriksen & Rosenthal, 2010). Given the importance and scale of this program, many scholars have evaluated its impacts on households and communities. Scholars have found that when LIHTC units are built in high-income neighborhoods and higher-priced housing markets, they have a negative impact on home sale prices while having the opposite effect in low-income neighborhoods and more stagnant housing markets (Diamond & McQuade, 2019; Woo et al., 2016).

As far as their influence on poverty concentration, when LIHTC units are built in high-poverty areas, they tend to reduce neighborhood poverty, likely by inducing in-migration of higher income families, while having no significant spillover effects in low- and moderate-poverty neighborhoods (Ellen et al., 2016). When considering the racial composition of neighborhoods, Diamond and McQuade (2019) affirmed property price decreases in affluent white neighborhoods, but found that high-income, high-minority areas observed stable prices

when LIHTC units were developed there. Additionally, they found areas near LIHTC developments show increases in nonblack home purchases.

A possible exception to this general relationship between LIHTC development and property values is described in Schwartz et al.'s (2006) case study of subsidized housing development in New York City. They found that property values adjacent to subsidized housing developments increased in general, though property values increased more in distressed neighborhoods. They also find that the tenure type of units in the subsidized project has an effect on changes in neighboring property values: subsidized projects with a higher proportion of rental units have a smaller effect on property value increases than subsidized projects with a higher proportion of for-sale units.

Researchers have also found LIHTC to be an important source of housing for tenants receiving assistance (like Housing Choice Vouchers) as well as very low-income tenants who do not have assistance (Williamson et al., 2009; Ellen et al., 2016). Since voucher holders can be vulnerable to rent increases and displacement if their base rent already exceeds the local payment standard, LIHTC units may be of particular importance to voucher holders in areas with increasing rents; perhaps even more so given that rising rents in those cases were associated decreases in poverty (Ellen & Torrats-Espinosa, 2020). This is important, as researchers have affirmed the benefits of access to low-poverty neighborhoods to low-income households, increasing household incomes (Dastrup & Ellen, 2016) and improving outcomes for young children (Chetty et al., 2016; Ding et al., 2016; Dragan et al., 2019).

While LIHTC is the largest housing production program in the U.S., there has also been a lot of research on the efficacy of other programs and policies on inducing the production of housing to improve housing affordability. While there is a good deal of research about the

efficacy of state and local policies to improve housing production and affordability (e.g., Bento et al., 2009; Freeman & Schuetz, 2017; Hamilton, 2021; Krimmel & Wang, 2023; Marantz & Zheng, 2020; Phillips, 2024; Schuetz et al., 2009, 2011; Wang & Fu, 2022), this study primarily analyzes national data and market-level characteristics in ways that makes evaluating state and local programs outside the general scope of the project. In the event that such policies seem relevant or important for any of the analyses outlined in future chapters, they will be explicitly discussed and outlined in those sections.

2.3 Summary

In sum, numerous researchers have found evidence that links housing supply to housing costs (and filtering) in various ways. This has included research that follows household moves in relation to new market-rate developments (Mast, 2023), how prices of existing housing varies depending on its proximity to new market-rate developments (Asquith et al., 2020), and how filtering rates vary across housing market and unit types (Liu et al, 2021; Rosenthal, 2014; Spader, 2024; Weicher et al., 2017). However, there are important caveats to these conclusions as well as several important outstanding questions.

To start, recent research on filtering dynamics amongst unsubsidized housing units (Spader, 2024; Weicher et al., 2017) has not accounted for units developed under the country's largest subsidy program, LIHTC, due to data limitations. Second, while there has been some evaluation of how filtering varies by geographies and market types, little is known about how filtering varies by household characteristics (e.g., race/ethnicity). Given research on other portions of the housing literature finds that interventions like evictions and affordable housing development impact Black and Hispanic/Latino households differently, it is worth evaluating how filtering dynamics may vary as well. Lastly, filtering dynamics have typically been

evaluated by defining affordability at a certain threshold (e.g., 30% of 50% of AMI) or a decline in an incoming household's real income over time. These measures do not necessarily indicate that filtered units are more affordable than the households that occupy them or that filtering is equally effective at all tiers of the housing market (e.g., units affordable at 30% of AMI versus 80% of AMI). While some researchers have included other tiers as part of their analyses (Weicher et al., 2017), few have quantified filtering variation between housing market segments (Spader, 2024).

CHAPTER 3: Methodology

This section will provide an overview of the data sources that will be used, the general research design of this project, and a description of how filtering will be measured. The use of AHS data to track changes in housing affordability over time builds off of prior research (Spader, 2024; Weicher et al., 2017), so many of their processes will be replicated or inform my own design. Of particular note is the last subsection (*3.3 Filtering Measures*), which provides a detailed description of the method of measuring filtering, each having their own benefits and drawbacks. Using both methods and comparing results is another contribution of this study as a direct comparison has yet to be made by other researchers.

3.1 Data Sources

Primarily, this study will use data from the U.S. Census Bureau's American Housing Survey (AHS), which provides longitudinal unit-level information on a representative sample of housing units. Data from the AHS will be supplemented with other data from the U.S. Census Bureau and HUD. Below is a description of these datasets, including a description of their relevant variables, limitations and how they relate to the other datasets.

3.1.1 American Housing Survey (AHS)

The AHS has two types of datasets, a national file and metropolitan files for cities that are published in that survey year. Since 2015, the AHS has published data for 15 large CBSAs every survey year and an additional 10 CBSAs out of a pool of 20. This means 15 CBSAs are published every survey year while another 20 are published every other survey year (10 each survey year). AHS currently publishes surveys every other year so there is a new dataset file every other year for the national panel and 15 large CBSAs while the other 20 CBSAs are

updated every four years. In the national file an observation is representative of a certain number of housing units nationally whereas a metropolitan file's observations are representative of housing units in that CBSA. There are also two versions of each of these datasets, a Public Use File (PUF), which is available for public use and can be downloaded from the AHS website, and an Internal Use File (IUF), which includes private geographic information and is only available for use as part of an approved project through a Federal Research Data Center (RDC).

The Public Use File (PUF) is a publicly available version of the AHS national and metropolitan datasets. This data does not include any geographic information more specific than the Office of Management and Budget's (OMB) Core-Based Statistical Areas (CBSA). At that, CBSA information is only available for observations that are part of the published CBSA surveys, which is limited to 35 total CBSAs. As mentioned above, only 25 of these MSAs are available each survey cycle, as 10 MSAs from a pool of 20 are rotated each survey year. There is also a geographic identifier for Census Region and Division⁵ in the PUF. Starting on the following page is a comprehensive list of both the CBSAs and Census Regions/Divisions.

AHS published CBSAs⁶:

1. Atlanta-Sandy Springs-Roswell, GA
2. Boston-Cambridge-Newton, MA-NH
3. Chicago-Naperville-Elgin, IL-IN-WI
4. Dallas-Fort Worth-Arlington, TX
5. Detroit-Warren-Dearborn, MI
6. Houston-The Woodlands-Sugar Land, TX

⁵ See [this map](#) for further detail of which states make up these divisions and regions.

⁶ **1-15 are published each survey year**; 16-25 are published every other survey year, including 2015, 2019, etc.; 26-35 are published every other year, including 2017, 2021, etc. [AHS documentation linked here.](#)

7. Los Angeles-Long Beach-Anaheim, CA
8. Miami-Fort Lauderdale-West Palm Beach, FL
9. New York-Newark-Jersey City, NY-NJ-PA
10. Philadelphia-Camden-Wilmington, PA-NJ-DE-MD
11. Phoenix-Mesa-Scottsdale, AZ
12. Riverside-San Bernardino-Ontario, CA
13. San Francisco-Oakland-Hayward, CA
14. Seattle-Tacoma-Bellevue, WA
15. Washington-Arlington-Alexandria, DC-VA-MD-WV

“Next 20” published every other survey year

16. Cincinnati, OH-KY-IN
17. Cleveland-Elyria, OH
18. Denver-Aurora-Lakewood, CO
19. Kansas City, MO-KS
20. Memphis, TN-MS-AR
21. Milwaukee-Waukesha-West Allis, WI
22. New Orleans-Metairie, LA
23. Pittsburgh, PA
24. Portland-Vancouver-Hillsboro, OR-WA
25. Raleigh, NC
26. Baltimore-Columbia-Towson, MD
27. Birmingham-Hoover, AL
28. Las Vegas-Henderson-Paradise, NV

- 29. Minneapolis-St. Paul-Bloomington, MN-WI
- 30. Oklahoma City, OK
- 31. Richmond, VA
- 32. Rochester, NY
- 33. San Antonio-New Braunfels, TX
- 34. San Jose-Sunnyvale-Santa Clara, CA
- 35. Tampa-St. Petersburg-Clearwater, FL

Census Regions (higher level) and Divisions (lower level)

- A. Northeast
 - a. New England
 - b. Middle Atlantic
- B. Midwest
 - a. East North Central
 - b. West North Central
- C. South
 - a. South Atlantic
 - b. East South Central
 - c. West South Central
- D. West
 - a. Mountain
 - b. Pacific

The Internal Use File (IUF) is not publicly available and required the approval of a proposal from a Census Research Data Center. This data includes more specific geographic data (e.g., address, census tract, county, etc.) that would allow for (a) imputation of LIHTC data and (b) more granular analysis of the data (e.g., how filtering rates on minority-majority or low-income tracts compare to other areas). Additionally, access to this dataset is necessary to know what the AMI is for observations in the national dataset (which do not contain geographic

identifiers for CBSA) as only observations from the metropolitan datasets have AMI information.

For both these datasets, there are numerous variables that are of interest for the analyses in this study. There are variables describing household characteristics, including race/ethnicity and household income, unit characteristics, including quality issues or whether it is subsidized, and neighborhood characteristics. Given the focus of this study is how filtering varies across BIPOC households and various income tiers, those variables are critically important. Fortunately, those variables are available in both the PUF and IUF, making it possible to answer many of the research questions without necessarily gaining access to the IUF. Specific variables and their definitions will be available in *Chapters 4, 5, and 6*, which describe the research questions, measures, variables, etc. for each of the analyses in detail.

3.1.2 Supplemental data sources

Several sources of data outside of the AHS will provide necessary information to make some of the analyses in this study possible. Below is a brief description of additional datasets identified and what they may be used for in the context of this project.

HUD's Income Limits documentation. This dataset provides the AMI for different areas/metropolitan areas across the U.S.⁷ This data may be used more to verify proper AMI levels are being used but may be redundant if access to the IUF is attained, as it includes AMI as a variable. In the event that IUF data is not available, there are ways to estimate an observation's AMI using an algorithm developed by Weicher et al. (2017), in which case this dataset would also be of use.

⁷ See https://www.huduser.gov/portal/datasets/il/il2023/select_Geography.odn

American Community Survey and Decennial Census data. Data from the U.S. Census Bureau can provide demographic data for different geographic areas. This is specifically useful in the event that I gain access to the IUF and can evaluate how filtering varies across different types of geographies (e.g., high- and low-income areas). This dataset will also be useful in controlling for market characteristics (e.g., concentration of affordable housing units) and total housing unit growth by metropolitan region.

HUD's LIHTC property-level dataset. This dataset will be used if access to the IUF is granted in order to remove LIHTC units from the analysis of filtering of market-rate housing units. This data may also be useful as part of an analysis of filtering trends at both the national and CBSA levels, specifically understanding how filtering rates change depending on differing levels of LIHTC presence or development.

Federal Housing Finance Agency (FHFA) Price Index. This dataset provides indices for single-family home prices in the United States for various levels of geography, going back to the mid-1970s for all 50 states in the U.S. This index is available at the national, census division, state, metro area, county, ZIP code, and census tract levels and uses a repeat purchase method to calculate these indices. While this study focuses on the rental market in particular, these indices are useful in understanding how home prices are fluctuating in specific markets, which likely influence filtering and rental market dynamics in general.

Zillow Home Value Index (ZHVI). This index developed by Zillow will be utilized as an additional measure of how home prices have changed over time at the CBSA-level. This measure looks at how home value and market changes evolve over time for homes in the 35th to 65th percentile range.

Zillow Observed Rent Index (ZORI). This is another index from Zillow, which will be utilized in order to measure specifically how rents are increasing over time at the CBSA-level. This measures changes in repeat index and weights observations in order to ensure representativeness of the entire rental stock. This also utilizes rents in the 35th to 65th percentile range and weights those observations to reflect the general rental stock.

3.2 Research Design

This will be a longitudinal study of housing units nationwide (and in large U.S. cities) that tracks and analyzes shifts in affordability and tenure over time. This is made possible by the AHS dataset, which collects longitudinal data on housing units every two years for its national sample as well as its sample of 15 large cities and every four years for an additional 20 large cities. Following Weicher et al. (2017), and using HUD-defined affordability⁸ levels, affordable units are defined as those where rents are 30 percent or less of gross income for households earning up to 50 percent of Area Median Income (AMI). In addition to defining affordability relative to a static threshold, I will also replicate the repeat income model used by recent researchers who have quantified the prevalence of filtering (Liu et al., 2022; Rosenthal, 2014; Spader, 2024). The specifics of how filtering will be measured using these two approaches (threshold and repeat income) is detailed in *Section 3.3 Filtering Measures*.

3.2.1 Time frame for analyses and data availability

This analysis will use AHS data from 2015 onward. This time frame is selected for two reasons. First, it updates past analyses that focused on earlier time frames, specifically 2013 and earlier (Liu et al., 2022; Rosenthal, 2014; Weicher et al., 2017). In addition to better

⁸ HUD defines housing as affordable when it costs 30 percent or less of a household's income: <https://www.huduser.gov/portal/datasets/home-rent-limits.html>

understanding current filtering dynamics, there is also the issue of the 2008 financial crisis that may have impacted filtering dynamics in the short run either via supply changes or downward shifts in renter incomes (Collinson, 2011). Second, the AHS made changes to their national sample in 2015⁹, making data in 2013 and prior incomparable to data in 2015 and onward. As such, 2015 would then be the base year of data for this project.

This project utilized AHS data through 2023, with the most recent survey year (2023) becoming available in late 2024. Therefore, this study uses 2015 as the base year and units are tracked through the 2023 dataset, which would include survey years 2017, 2019, 2021, and 2023.

3.2.2 Unit of analysis: housing units

The unit of analysis for this study is a housing unit. This is the unit of observation for the AHS and housing units will be tracked over time to observe changes in affordability. The AHS selects units that are representative of a larger number of units, so weights will be used in all analyses—unless otherwise stated, base year (2015) weights will be used for all analyses. Regardless, this study is focused on analyzing unit-level changes and characteristics unless otherwise specified. This distinction is important because some housing programs are tenant based, but AHS data follows housing units rather than households. This means that portable vouchers are less relevant to this paper, for example, since they keep housing costs affordable to households rather than preserving the affordability of particular units over time.

3.2.3 Identifying assisted units

Unless specified otherwise, this study analyzes filtering dynamics for unassisted and unsubsidized housing units in the United States. As a result, the AHS data being used in this project need to have publicly subsidized and assisted units removed for a more accurate

⁹ Changes in survey methodology between 2013 and 2015 are outlined [here](#). Spader (2024) also notes this changes as a reason for not comparing post-2013 data to prior years.

quantification of filtering dynamics for market-rate housing units. Fortunately, AHS has matched their observations to HUD data on units receiving federal subsidies. This variable is coded as “RENTSUB” and includes the following response codes (and their definitions) below:

- (1) *Public housing*: the unit is owned or managed by a public housing authority.
- (2) *Portable voucher*: the householder has a voucher, and it can be used in another location.
- (3) *Non-portable voucher*: the householder has a voucher, and it cannot be used in another location.
- (4) *Other government subsidy*: the householder’s rent is lower because of a governmental program or is paid in part by federal, state, or local government.
- (5) *Rent reduction requiring annual recertification not reported elsewhere*: the householder has to recertify to determine their rent level.
- (6) *Rent reduction because household member works for owner*: the householder receives discounted rent because a household member works for the unit owner.
- (7) *Rent reduction because household member related to owner*: the householder receives discounted rent because a household member is related to the unit owner.
- (8) *No rental subsidy or reduction*
- (M or -9) *Not reported*
- (N or -6) *Not applicable*

The longitudinal panel used for the analyses in *Chapters 4* through *6* removed observations with response codes (1) Public housing, (3) Non-portable voucher, and (4) Other government subsidy; which effectively removes all observations where subsidies are tied to specific *units*. However, the regression analyses utilize variables that identify whether a unit is

rent controlled¹⁰ and/or is occupied by tenants utilizing vouchers. Since portable vouchers move along with the householder, they do not factor into my analyses of whether rental units “are affordable in and of themselves” (Weicher et al., 2017, p. 36). Rent control policies are worth controlling for at the unit level, but this policy is also not a direct subsidy to the unit, meaning these units are still privately financed, maintained, etc. and are part of the NOAH in the U.S.

Weicher et al. (2017, p. 136) point out that the AHS does not identify units receiving a tax subsidy, possibly meaning numerous units derived from the largest housing construction program, LIHTC, are not accounted for in AHS data. As mentioned above in *3.1.2 Supplemental data sources*, IUF access provides the opportunity to identify LIHTC units by matching HUD’s LIHTC property-level dataset¹¹ to AHS observations. While this study is focused on rental housing units, owner-occupied housing units will be tracked as well since they can eventually enter the rental housing market in the event of shifts in tenure.

3.2.4 Identifying household turnovers

The repeat income model (see *3.3.1*) requires that a unit’s occupants turnover in order to measure the change in real income between the initial household and the incoming household. Fortunately, the AHS has a variable “SAMEHHLD” that indicates whether the current household members are the same as those occupying the unit in the previous survey year. Response codes for this variable include:

- (1) All household members the same as previous interview year
- (2) Some household members added or removed
- (3) All household members different than previous interview year

¹⁰ Where variable “RENTCNTRL” = 1: Yes

¹¹ HUD has a database of “52,006 projects and 3.55 million housing units placed in service between 1987 and 2021” <https://www.huduser.gov/portal/datasets/lihtc/property.html>

- (4) Prior interview year was not a regular, occupied interview
- N or -6: Not applicable

For the purpose of this analysis, a turnover will be defined as a situation where all household members are different than the previous interview year (i.e., response code 3). While shifts in some household members may alter household incomes, such shifts would likely be driven by whether or not added or lost household members were of working age rather than changes in occupant incomes due to the age and/or quality of the housing unit.

3.2.5 Geographic levels of analysis

This analysis will include evaluating filtering by CBSA to understand how filtering dynamics differ by housing markets. This is achievable using the PUF when analyzing observations from the published metropolitan datasets (15 cities published every survey year and an additional 20 that are published every other survey year). As previously mentioned, Census Division and Region can be analyzed using the PUF as well for all observations. In the event that IUF access is obtained, comparing filtering variation by housing market type would be preferable.

There are a couple ways to categorize geographies in order to analyze filtering variation. For example, Somerville and Holmes (2001) quantify housing market characteristics based on the concentration of affordable housing units in the base year while others have made comparisons by clustering CBSAs based on housing market characteristics (Spader, 2024). While these approaches have their own strengths, this project will generally utilize two-way fixed effects¹² and/or use market-level variables to measure differences for all housing units in the U.S. Given the focus on rental units in particular, there often will be “renter-end”

¹² Two-way fixed effects are used in *Chapter 4* while CBSA-level variables are used in *Chapter 5* and *Chapter 6*

specifications that only evaluate units that end as renter-occupied. Otherwise, retention of data (and the samples used) was prioritized for both the purposes of preserving statistical power in the more specific analyses and meeting FSRDC disclosure requirements. CBSA-level variables include housing unit growth, which will be based on changes in unit counts between the 2010 and 2020 decennial census using 2010 boundaries¹³. Other supply and cost variables used were generally tied to CBSA-level geography, though gentrifying tracts were identified using IUF data in order to identify whether a given unit is on a tract experiencing demographic change or not.

3.3 Filtering Measures

Filtering has been measured in recent research using two different methods. The first method quantifies the change in real household income over time for units whose occupants have turned over (i.e., a new household has moved into the unit at some point). For this method, filtering is quantified by the amount that real income changes over time so downward filtering would be associated with a negative change in real income. The second method is measuring changes in gross rent relative to a specific rent threshold. The rent threshold is typically one of HUD's affordability tiers, often a rent level equivalent to 30 percent¹⁴ of 50 percent of AMI. Using this method, a unit is considered to have downward filtered if it was above the threshold in the base year (e.g., rent was greater than 30 percent of 50 percent of AMI) but was below the threshold in one or more subsequent years (e.g., rent was less than 30 percent of 50 percent of AMI in later years).

¹³ 2010 boundaries are used for the AHS data used in this analysis, so using those boundaries for unit growth is most appropriate for comparison purposes.

¹⁴ The 30% portion is based on HUD's threshold for household's being "rent burdened". For example, a household earning \$30,000 per year would be considered rent burdened if they paid more than 30% of their income, or \$9,000, per year on rent (i.e., if their monthly rent exceeded \$750, they would be considered rent burdened).

Each of these measures have benefits and shortcomings. Affordability is not solely determined by either of these measures since a household's income and their gross housing costs combine to determine whether or not their housing is affordable. Even if a unit's occupying households have lower real incomes in future years, it is not clear whether that housing is actually affordable to them (i.e., whether they are rent burdened or not). Similarly, an increase or decrease in gross rents over time does not necessarily indicate that the households occupying a unit can afford that unit. However, both these measures also have clear merits as it relates to measuring filtering. Changes in real household incomes over time is important to understand in the context of understanding the impact of increases to housing supply over time. If existing supply is opening up to lower income households more persistently in regions with larger gains in housing supply, that would indicate filtering is effective in providing more housing options for lower income households over time. Similarly, understanding how effective filtering is at producing units affordable at specific affordability tiers, regardless of household incomes of occupants, is important to determine whether filtering can effectively meet needs at specific segments of the housing market or not.

In part because of their individual strengths (and weaknesses) and because, to my knowledge, the outcomes from using methods have not been compared in prior research, I will use both methods and compare results. The details of how I will measure filtering using each of these approaches is described below.

3.3.1 Repeat income model

To use the repeat income model, units that turn over at least once within the timeframe analyzed (2015 to 2023) were identified, similar to prior researchers (Liu et al., 2022; Rosenthal, 2014). Additionally, this analysis uses Spader's (2024) first-last approach that

measures changes in income at the unit-level by comparing the income of the household in the last turnover to that of the household in the first turnover. This eliminates possible selection bias from units that turnover frequently and would therefore have numerous turnover pairs; as such, a given unit with at least one turnover (i.e., units remaining in this sample) will only have one point estimate of change in income. For these units filtering outcomes will be measured in two ways:

- *The relative change in real household income.* To control for inflation, nominal household income will be converted to 2015 dollars, using the Consumer Price Index (CPI) provided by the Bureau of Labor Statistics (BLS). The measure of change in real income will be the mean logged change in household income between the initial household occupying the unit and incoming household (i.e., a given turnover pair). So, if a unit has an incoming household earning \$50,000 in 2015 dollars in 2017 and a final turnover in 2021 with an incoming household earning \$45,000 in 2015 dollars, the measure would be $\log(45,000/50,000) = -0.105$, or a -10.5% change in logged repeat income.
 - To account for different time lengths between turnovers, I will use Spader's (2024) method of normalizing this ratio by using the implied log 5-year change in household income to produce estimates of change in household income. Since the period in the previous example spans 4 years (2017 - 2021), the implied log 5-year change would be estimated as follows:
 - i. The raw 4-year change in household income would be normalized to the 5-year change in income. Therefore, the 45,000/50,000 base value would be adjusted to reflect the 5-year change by taking that ratio to the $5/n$

power— $5/4$ in this case since the number of years is 4. This would lead to a 5-year change in log household income of $\ln[(45,000/50,000)^{5/4}]$, or $\ln(0.9^{1.25})$ which equals $\ln(0.8766)$ or -0.1317 .

- *The number (and percentage) of turnover pairs that result in a decrease in household income.* To understand more broadly what share of all units are filtering downward, this is simply a measure of the number (and ratio) of first/last turnover pairs that have a negative value (i.e. decrease in household income). These results will quantify the magnitude (and percentage) of units filtering downward over time.

As a result, the repeat income analysis will estimate the overall logged 5-year change in real household income as well as the overall number (and percentage) of units that end up with lower-income occupants over time. While other researchers have limited this measure to units with multiple turnovers, this study will include a single-turnover, multi-turnover, and pooled specification, the latter of which is inclusive of all types of turnovers.

3.3.2 Gross rent threshold

Following Weicher et al. (2017), this method will assess whether a unit is affordable or not in the base year and subsequent years of the analysis. Affordability is defined as gross rent being equal or less than 30 percent of HUD's very low-income income threshold (i.e., 50 percent of AMI). AMI levels shift over time so rent can grow some amount year over year while remaining affordable depending on how its increases compare to AMI increases over time. For example, if a city has an AMI of \$100,000, a unit would be affordable at the 50% of AMI level if its monthly rent was less than or equal to 30% of \$50,000 (i.e. 50% of AMI), or \$1500 per month. If six years later the AMI is now \$120,000 then that unit will still be classified as affordable if it is equal to or less than 30% of \$60,000 (i.e., 50% of the new AMI), or \$1800 per

month. Of note, 50% of AMI (or other thresholds) rent levels are adjusted based on the number of bedrooms in the unit¹⁵ (and implied number of household members). Since the AHS dataset has a variable for the number of bedrooms, the appropriate HUD rent tier was applied to the unit based on the number of bedrooms and the corresponding CBSA affordable rent levels.

Using this method, changes in affordability are categorized for units included in the analysis within a discrete number of outcomes. The outcomes used in the various analyses in this study vary by the unit's initial state (i.e., whether it starts off as affordable or unaffordable). For units that are affordable in the base year (2015), outcomes include:

- *Always Affordable*: units that are affordable in both 2015 and 2023
- *Filtered Upward*: units that are affordable in 2015 and unaffordable in 2023

For units that are unaffordable in the base year (2015), outcomes would include:

- *Always Unaffordable*: units that are unaffordable in both 2015 and 2023
- *Filtered Downward*: units that are unaffordable in 2015 and affordable in 2023

For most of the analyses using this method, these outcomes will be aggregated and reported as the total number of affordable and unaffordable housing units. For example, I will report the number of affordable units in the base year that become unaffordable over time (i.e., number of upward filtered units) as well as the number of unaffordable units in the base year that become affordable over time (i.e., the number of downward filtered units). Also, the total number of units that are affordable in the beginning year (2015) and final year is quantified at times to understand how the total NOAH stock is trending over time. Since there are more unaffordable units than affordable units, quantifying total units added (i.e., downward filtered) and lost (i.e., upward filtered or removed from rental stock) to the affordable housing stock is

¹⁵ See <https://www.huduser.gov/portal/datasets/fmr/fmr2026/FY26-Public-FMR-Methodology.pdf>

more useful than using average percentages to assess shifts in total NOAH stock. The regression analyses for the gross rent method generally evaluate whether the unit ends as affordable or not without delineating whether units begin as affordable or not, though the beginning affordability status is included as a control variable.

Despite AMI being unavailable in the PUF, preliminary descriptive analyses were done only on the metropolitan areas within the integrated national dataset¹⁶, specifically in *Chapter 4* where outcomes across CBSAs are compared. However, access to the IUF was attained and most analyses were able to identify the affordability of all units in the sample (i.e., whether they were affordable at 50% of AMI in base and final years or not).

Regardless of the specific approach used to assess changes in gross rent, there are potential benefits of using gross rent as opposed to the repeat income approach. One of the benefits of this measure is that it retains all observations in the sample as it does not require multiple turnover pairs as in the repeat income approach¹⁷. This means tabulations of these results are inherently more likely to retain statistical power and have more narrow confidence intervals.

3.4 Notes about the AHS

The AHS is a complex random survey, which in the case of the AHS involves taking a sample and then weighting observations based on several stratifications. This survey design has some implications for this study that are worth noting. Below are a couple areas worth being aware of going forward, as they will impact how the various analyses in this study will be carried

¹⁶ See 3.1.1 for a full list of the 15 metropolitan areas surveyed every cycle that are included in the integrated national sample

¹⁷ The gross rent sample has about 42,000 observations while the repeat income sample has about 17,000 observations

out in practice. Specifically, I want to discuss broadly how AHS weighting is done and, subsequently, how that impacts estimations of subpopulations.

3.4.1 Weighting

Before discussing how estimations of subpopulations within the AHS dataset are to be done, it is important to understand the general design of the survey. The primary sampling units (PSU) of the AHS are based on geography, with 85 PSUs coming from the 85 largest CBSAs and another 224 PSUs that are stratifications of the 1,699 counties located outside the 85 largest CBSAs. From these PSUs (309 in total), just over 95,000 units were selected in a stratified sample that ensured they were representative of units within each PSU.

After this sample is selected, a base weight is determined based on the probability a given unit had of being selected into the sample. From there, weights are adjusted based on several factors, including:

1. Calibrating AHS estimates of total housing units to independent Census Bureau estimates within each stratum.
2. Adjusting for interview non-responses
3. Adjusting for housing and demographic factors, including:
 - a. Number of newly constructed units (by Census Region)
 - b. Total persons (first by state, then CBSA/place)
 - c. Black persons (first by state, then CBSA/place)
 - d. Persons aged 65+ (first by state, then CBSA/place)
 - e. Hispanic persons (first by state, then CBSA/place)
 - f. HUD-assisted units (first by state, then CBSA/place)
 - g. Occupied units (first by state, then CBSA/place)
 - h. Vacant units (first by state, then CBSA/place)

Importantly, the aforementioned strata are the only ones accounted for in the survey design. Strata for household income and ethno-racial characteristics (outside of Black persons and Hispanic persons) are not part of the survey design. Since these subpopulations are important to several of my analyses, the next subsection describes the implications of this design.

3.4.2 Estimating subpopulations (custom tabulations)

Estimating subpopulations in a complex survey that has not stratified its sample based on those subpopulations requires some additional statistical work. The fundamental reason this is an issue is that estimating subpopulations that have not been accounted for in stratification means that their probability of being selected into the sample has not been accounted for in the weights being used. For example, while Black and Hispanic persons are strata in the AHS design, other ethno-racial groups (e.g., Asian, Pacific Islander, and American Indian or Alaska Native) may have high margins of error that could make results insignificant¹⁸. Similarly, clustering geographies or tabulating by household income are strata not included in the design so the calculations of margins of error are not straightforward.

Fortunately, there are fairly simple workarounds to deal with this issue using R software¹⁹. Namely, this involves subsetting the subpopulation of interest from the total sample while using the entire population to estimate standard errors. There is a survey package in R (“survey”²⁰) that makes analyses of subpopulations in this study possible, including regressions like those done in *Chapters 4 to 6*²¹ by utilizing AHS-provided replicate weights. These “*can be used to estimate variances for most estimators, including means, totals, ratios, and regression*

¹⁸ Personal email communication between the author and AHS analysts, February 2024

¹⁹ See *Complex Surveys: A Guide to Analysis Using R* by Thomas Lumley, p. 32 in Chapter 2 <https://onlinelibrary.wiley.com/doi/book/10.1002/9780470580066>

²⁰ See <https://r-survey.r-forge.r-project.org/survey/> for details about this package (written by Thomas Lumley). This includes details about how to use replicate weights and subpopulation estimations.

²¹ See this UCLA white paper <https://stats.oarc.ucla.edu/r/seminars/survey-data-analysis-with-r/>

coefficients” per HUD and U.S. Census Bureau provided guidelines²² instead of using primary sampling units (PSUs) and strata to estimate variance. While point estimates of variables are typically the same using these packages, margins of error are typically higher, so the confidence intervals will be wider. Given the large size of the datasets (~65,000 for the National Sample; ~2,000 for Metropolitan Samples), I don’t foresee this as an issue, particularly because most outputs are aggregated nationally on certain characteristics (i.e., percentage of affordable units with inadequacy issues compared to percentage of unaffordable units with inadequacy issues nationally), which retain as much statistical power as possible. The only smaller geographical outcomes that are reported are the aforementioned 15 CBSAs in the integrated national dataset. These CBSAs are oversampled and have large numbers of observations, but these results are of lesser focus and meant to be directional in comparison to other aggregated outputs that draw on the entire national dataset.

²² See https://www.census.gov/content/dam/Census/programs-surveys/ahs/tech-documentation/2015/Quick_Guide_to_Estimating_Variance_Using_Replicate_Weights_2009_to_Current.pdf

CHAPTER 4: Filtering and the importance of unsubsidized housing to low-income households nationally

4.1 Introduction/overview

This analysis will evaluate the role and magnitude of filtering nationally. One portion of the analysis will evaluate the magnitude of filtering as a source of housing affordable to households earning less than 50% of AMI. In addition to evaluating filtering's efficacy at making units affordable at that threshold, relative changes in household incomes (i.e., how real household income for occupant households changes over time) will also be measured using the repeat income method. As part of this analysis of the national housing stock, filtering's relationship with several housing unit characteristics will also be evaluated. Ultimately, the aim of this analysis is to better understand the role and significance of the nation's unsubsidized housing stock in providing affordable housing to low-income households.

For more detailed information on how filtering will be measured using the two approaches, see section 3.3 *Filtering Measures*. The following section will outline the characteristics that will be used to tabulate the data and how filtering outcomes will be reported in order to better understand the phenomenon's importance to providing housing that is affordable to low-income households.

4.2 Measures and variables

Some of this analysis will be descriptive in nature in an effort to better understand how filtering is occurring and to what magnitude nationally during the time period evaluated. Before tabulating results by various characteristics, this analysis will start in the broadest way possible

by evaluating filtering at the national level using the AHS national dataset. Since I am using two measures for filtering (see 3.3 *Filtering Measures*), this evaluation will be done in two ways.

1. For the *repeat income* method, I will look at every unit that has had at least one household turnover during the time period being analyzed and compare the real household income between the original household and the new household. For those that have multiple turnovers, I will compare incomes between the first and last household²³.

The results of this analysis will be reported in three ways.

- a. Overall change in real household income over time (expressed as 5-year log change in real income) for units with at least one turnover.
- b. Number (and percentage) of units (with at least one turnover) that had a negative change (i.e., shifted to lower income households) in real income.
- c. Overall change in real household income over time for units that had a negative change in real income.

These results will give some indication of (a) the magnitude of which filtering occurs in unsubsidized housing units nationwide, (b) how prevalent downward filtering occurs across all units nationwide, and (c) the magnitude of change in incomes for units that do filter downward.

2. For the *gross rent threshold* method, I will evaluate shifts in affordability for all housing units based on changes in gross rent over time. Using the same threshold as Weicher et al. (2017) units will be deemed affordable if their gross rent is less than or equal to 30 percent of 50 percent of AMI. The results of this analysis will be reported in three ways.

²³ Following Spader's (2024) first-last approach

- a. Number of affordable units lost during the time frame analyzed. This will be calculated by measuring the number of units that were affordable at the 50 percent of AMI threshold and quantifying the number of those that were no longer affordable by the end of the time period analyzed. This will give me an estimation of the total number (and percentage) of affordable units that filtered upward during this time period.
- b. Number of unaffordable units that became affordable during the time frame analyzed. This will be calculated by measuring the number of units that were unaffordable at the 50 percent of AMI threshold in the base year and quantifying the number of those that became affordable by the end of the time period analyzed. This will give me an estimation of the total and percentage of unaffordable units that filtered downward during this time period.
- c. An aggregation and comparison of (a) and (b) to understand how the magnitude of upward and downward filtering compare and the number of overall additions and losses to the affordable housing stock during this time period. Losses due to removal from the rental housing stock should be separately accounted for.

While this broad analysis will give a first look at how filtering is impacting the nation's affordable housing stock over time broadly, there are many policy questions that can be answered by tabulating and evaluating filtering dynamics in several ways.

4.3 Policy questions

While understanding generally how prevalent filtering is and its relative impact (e.g., net additions/losses or percentage of units that filter downward), there are several policy related questions this dataset can help answer. Below are several questions that can be answered by further extending the initial analysis outlined in 4.2. Each of the following sections describe a relevant policy question as well as the empirical strategy to respond to that question.

4.3.1 How many (unsubsidized) units in 2015 filtered downward by 2023?

This is the overarching question of this analysis, which is answered using the empirical strategy outlined in 4.2. The policy relevance of this question is clear—understanding how prevalent filtering is as a phenomenon will better inform expectations around the relative efficacy of increased housing supply as a solution to affordability issues. In addition to the previously outlined empirical approach, a couple other outcomes will be reported to better understand the relative importance of filtered units to the affordable housing market. A couple such outcomes of interest include:

- (a) How many more (or less) affordable units are there in 2023 compared to 2015?
- (b) How do the net increases (or losses) in affordable units vary by geography (e.g., Census Division, CBSA)?

These questions can be answered by first quantifying the units that filtered downward by 2023²⁴, same as the process described in 4.2.

4.3.2 How do filtering rates for market rate units vary by unit age (i.e., are older units always more likely to filter downward)?

²⁴ For the repeat income method, this would be the number of units where real household income decreased; for the gross rent threshold method, this would be the number of units that became affordable at 50% of AMI

One of the central underlying theories of downward filtering is the idea that units age their rents (or purchase prices) decline. This could be driven by lack of amenities compared to newer units, degradation of the unit over time, etc. In practice, however, the filtering process is less linear. Researchers have actually found evidence that older units are less likely to filter downward and may even be more likely to filter upward, even when controlling for whether renovations or improvements were done on a unit. In fact, there may even be evidence that there is a “U-shaped relationship” between building age and rents—where prices fall up to a certain age of the unit before rising again for older, historic units—in urban rental markets with large numbers of historic units (Palm et al., 2020; Skaburskis, 2006).

This analysis aims to better understand the relationship between filtering and unit age in the United States²⁵. By tabulating the data already analyzed in the earlier analyses of this chapter by unit age²⁶ I can better understand how building age relates to filtering rates in the United States. Specifically, I plan to tabulate the data by building age (by decade) and recalculate the outcomes outlined in the earlier portion of this chapter to understand how filtering dynamics differ by building age. This analysis could also be replicated after removing units that have been recently rehabbed²⁷ from the dataset to control for recent renovations. A couple specific follow-up questions this analysis will aim to answer include:

- (a) How does downward filtering vary across unit age ranges?
- (b) Where are the largest clusters within the age distribution for downward filtered units and what does that say about how long it might take units to filter downward?

²⁵ Palm et al. (2020) studied Melbourne, Australia while Skaburskis (2006) studied Canadian cities

²⁶ AHS variable “YRBUILT,” which is a categorical variable based on decade the unit is built (e.g., 1990 represents units built from 1990 to 1999 while 2000 represents units built from 2000 to 2009)

²⁷ AHS variable “GUTREHB,” which is a yes or no response to the question “Has this housing unit undergone a gut rehabilitation in the last 10 years?”

(c) Is there an age threshold where units begin to filter up? Do units eventually filter up as they age?

There are numerous other ways this could be further contextualized to better understand the role of unit age in different contexts (e.g., suburban vs. central city, different affordability tiers, neighborhood characteristics, etc.), but those follow-up analyses are more suited for and evaluated in *Chapters 5 and 6*.

4.3.3 Does filtering provide adequate quality housing for very low-income households? How prominent is substandard housing amongst units that filter to very low-income households?

As mentioned in 4.3.2, filtering is thought to occur as units age and even degrade in quality. Therefore, even if units are filtering downward to lower rents or lower-income households, there may still be a question of whether or not those affordable units are actually of sufficient quality. Better understanding how the relative quality of a unit is impacting filtering is an important policy question for a couple reasons. First, there has been some evidence that unsubsidized affordable units can become too costly in terms of maintenance costs for landlords to retain profits (Garboden & Newman, 2012). If that does become the case, critically important affordable housing may be at risk of being demolished, abandoned, or otherwise removed from the housing stock. Second, if filtering is only able to supply units affordable to very low-income households if they are of particularly low-quality, it is an important caveat and consideration if NOAH for very low-income households is a goal of supply-side strategies.

The empirical strategy to evaluate these questions involves tabulating AHS data based on some number of unit maintenance related variables. The AHS includes variables on heating problems, electrical problems, plumbing problems, pests, whether a unit has had a gut rehab, is

of severe inadequacy, the number of upkeep problems²⁸ that exist, and others. While I may utilize more of these variables depending on what descriptive statistics say about the prevalence of them (e.g., if severe inadequacy is limited to 100 observations out of the tens of thousands of observations in the dataset, it may not be a useful measure). Below are some analyses and questions I believe would help answer the broader question of how housing quality relates to filtering.

- (a) Tabulate downward filtered units by adequacy or quality. Measures could be used for substandard (perhaps based on severely inadequate or upkeep measures) units and units of adequate quality (all other units).
 - (i) How do the adequacy measures for downward filtered units compare to subsidized affordable units?
 - (ii) How do the adequacy measures for downward filtered units compare to all other units?
- (b) Evaluate what happens to substandard units that exist in base year (2015) by the final year of the study period (2023).
 - (i) Are substandard units likely to be demolished, upward filter, remain affordable, etc.?
- (c) Quantify and compare filtering impacts (or totals) for units: (1) that are severely inadequate or have multiple upkeep issues, and (2) all other units.
 - (i) How different are filtering rates (and totals) between these types of units?

²⁸ *Adequacy*: Adequate, Moderately Inadequate, Severely Inadequate; *Upkeep*: Less than 3 upkeep problems, 3 or 4 upkeep problems, 5 or more upkeep problems

4.4 Hypotheses

Below are several hypotheses related to these analyses, some of which are in direct response to recent research on the same or similar topics.

- (1) *The proportion of rental housing stock that is affordable to lower income households (gross rent method) will decrease despite a slight uptick in downward filtered housing units (repeat income) during the time frame analyzed.* The mechanism driving this would primarily be the increasingly more expensive urban housing markets combined with recent trends of stagnating wages for low- and moderate-income households and a slowdown of multifamily construction post-recession (Collinson, 2011; Freeman & Schuetz, 2017; Spader, 2024). More specifically, there might be an uptick in downward filtered units by the repeat income measure, but I anticipate the gross rent threshold measure will show a loss of NOAH units.
- (2) *More affordable housing units will be lost from shifts in tenure than gained (i.e., more rental units will be converted to owner-occupied units than vice versa) and at a higher rate than in the 1985-2013 timeframe analyzed by Weicher et al. (2017).* This would align with recent trends in homeownership for low-income households, which have rebounded steadily since 2015. While this trend could very well be considered a positive development overall, NOAH units that were previously rentals may have shifted to owner-occupancy, reducing the affordable rental stock as a result²⁹. However, racial disparities still persist in homeownership rates (which are reflected in growth in

²⁹ See <https://www.minneapolisfed.org/article/2024/homeownership-among-lowest-income-households-climbs-near-all-time-high#:~:text=In%202023%2C%2047.1%20percent%20of,households%20have%20risen%20since%202015>

homeownership rates by race/ethnicity since 2015), meaning this trend could exacerbate rather than alleviate inequities in housing outcomes.

(3) *Units that are inadequate or have upkeep issues are more likely to both filter downward and be demolished.* NOAH that have maintenance issues have difficulty obtaining adequate financing in certain circumstances (Garboden & Newman, 2012), so these units may be rented as long as they can generate income before being demolished or otherwise removed from the rental stock (i.e., sold and/or flipped and converted to owner-occupancy or short-term rentals). Some scholars have found that a “U” shaped relationship between age of unit and filtering, with units filtering downward until around 50 years of age before changing course and filtering upward (Palm et al., 2020; Skaburskis, 2006). I believe units that are not purchased and flipped (i.e., shift to owner-occupied) will either be rehabilitated to be rented to higher income households (i.e., filtered upward) or allowed to degrade in quality (and filter downward) until they are demolished.

(4) *Downward filtered units will have higher rates of upkeep or inadequacy issues than unaffordable units.* The premise of filtering is that older units that may have degraded in quality eventually end up being occupied by lower-income households. For that to hold true, it would make sense for these units (downward filtered) to have higher rates of maintenance issues.

These hypotheses are related to filtering dynamics broadly and generally, as is the scope of this particular analysis. The next chapter outlines an analysis of spatial variation specifically with the aim of further contextualizing the filtering dynamics revealed in this analysis.

4.5 Nationwide trends in filtering, 2015 to 2023

In this section, I will quantify and describe filtering trends nationally from 2015 to 2023. In general, I expect my results to follow Spader's (2024) findings for more recent years (his analysis included a panel for 2015 to 2021) that show units are generally filtering upward both based on the change in real income and the percentage of units that have a decrease in real income. Similarly, I expect that more units will have filtered upward than downward during this time frame when using the gross rent threshold approach (i.e., more units will have become unaffordable at the 50% of AMI threshold than those that become affordable).

Using the panel I constructed from national AHS data (2015 to 2023), the mean change in logged income for unsubsidized units that turned over in that period will indicate the general direction (downward or upward) of filtering during that period. Additionally, the percentage of units with negative changes (i.e., downward filtered) in income will be calculated to show what percentage of these units filtered downward. For the gross rent threshold approach, I will calculate the share of units that shifted above/below the 50% of AMI rent threshold. This does not require units to have household turnovers since rent shifts can occur independent of household turnover and incomes.

To start, some descriptive statistics will be shown and evaluated. These data will be shown for both measures—repeat income and gross rent threshold. Ultimately, that information will help guide the subsequent regression analyses for both measures in sections 4.6 and 4.7. The conclusions section will briefly discuss the most relevant findings from the data outputs in this first section.

4.5.1 Descriptive statistics: national affordability trends

The initial results of the repeat income panel indicate that housing units are generally filtering upward from 2015 to 2023 nationally. This aligns with Spader’s (2024) findings and broader trends in housing cost appreciation nationally during this time frame³⁰. 4.5.1 shows a summary of these findings broadly, with results delineated both by the number of turnovers observed within an individual housing unit where “Single” refers to those with only one turnover while “Multi” refers to those with two or more turnovers during this time frame. As discussed in *Chapter 3*, prior uses of the repeat income measure (Rosenthal, 2014; Spader, 2024) have restricted their sample to units with two or more turnovers in order to compare incomes when households began to occupy a given unit. However, despite there not being data on the income for households in the year they began to occupy a unit, there is information on their income in the years they responded to the survey. To better understand both how filtering varies between single- and multi-turnover observations and whether such a restriction is necessary for this analysis, results are compared between these two specifications.

Overall, the logged five-year income growth rate (i.e., “change in *repeat income*”) is +15.40% nationally and statistically significant at the $p < 0.05$ level. However, this positive growth in overall incomes (i.e., “upward filtering”) is primarily driven by units with only a single turnover. Single turnover units have a change in repeat income of +17.81% while multi turnover units have a point estimate of +8.54% though it is not statistically significant at the $p < 0.05$ level.

As for the percentage of units that filtered downward (i.e., units with negative changes in repeat income), point estimates for pooled, single, and multi turnover units all had estimates of

³⁰ Since 2001, rent increases have far outpaced wage growth, see: <https://www.cbpp.org/media/renters-incomes-havent-caught-up-to-rising-housing-costs-4> and <https://endhomelessness.org/state-of-homelessness/>

less than 50%. Overall, the estimate for all units that filtered downward is slightly under 16 million units nationally while the estimate for upward filtered units was about 16.7 million units. Thus, about 0.7 million more housing units became less affordable compared to those that became more affordable over the study time period. As a result, this measure indicates that housing costs have been rising nationally since 2015 for occupants of existing market-rate units.

When using the gross rent threshold measure, the affordability trends look different compared to the results derived from the repeat income measure. As described in *section 3.3.2* of Chapter 3, the *Gross Rent Threshold* measure looks at how the affordability of a given unit changes over time. Specifically, this analysis will look at whether a given unit is above or below the 50% of Area Median Income (AMI) threshold in both the initial year (2015) and final year (the last year there is available data for housing costs from 2017 to 2023) of the analysis. This method has four discrete outcomes for a given unit, which are reiterated below:

- **Always Affordable (AA):** units that are affordable at the 50% of AMI threshold in both 2015 and the final year.
- **Always Unaffordable (AU):** units that are not affordable at the 50% of AMI threshold in both 2015 and the final year.
- **Upward Filtered (UF):** units that are affordable at the 50% of AMI threshold in 2015 but are no longer affordable at that level in the final year.
- **Downward Filtered (DF):** units that are *not* affordable at the 50% of AMI threshold in 2015 but become affordable at that level in the final year.

Using PUF data, data on the top 15 largest metropolitan areas were utilized for this analysis. While more thorough analyses that utilize IUF data will be presented in later chapters, this provides some initial insight into what general trends might be occurring throughout the

United States during the study period. *Table 1* (p. 60) shows how frequently these discrete outcomes occurred during this study period nationally. Importantly, these data are tied to all tenure types, not just rental units. So, if the housing costs for an owner-occupied unit are below the 50% of AMI rental level for that unit, then that unit would be flagged as an affordable unit.

The results indicate that the majority (more than 70%) of all units remain unaffordable (52.1%) or affordable (18.0%) throughout the study period. In terms of units that shifted above or below the specified affordability level, more units are filtering downward (18.3%) than are filtering upward (11.5%) during this study period. Overall, this subsample represented 32.7 million housing units across the 15 largest cities outlined in *Section 3.1.1* that are published in every AHS survey. Of these units, about 22.9 million remained affordable or unaffordable throughout the period of the study, 6.0 million filtered downward, and 3.8 filtered upward.

Overall, just over two million more units filtered downward than upward, indicating that the naturally occurring affordable housing stock increased by 23.0% during this time frame, from 9.7 million to 11.9 million units between 2015 to 2023. The median change in housing costs as a percentage of income (HCAP) from 2015 to the last year was an estimated -2.5%, indicating a slight downward change in housing costs relative to incomes. Nationally, incomes have generally risen three to four percent³¹ from 2015 to 2023, with large outliers occurring in 2020 and 2021, including amongst lower wage workers³². Similarly, HUD affordability levels have increased by roughly 4 percent per year during that period of time³³.

³¹ Social Security Administration, Average Wage Index: <https://www.ssa.gov/oact/cola/awidevelop.html>

³² St. Louis Federal Reserve, 1st Quartile wages: <https://fred.stlouisfed.org/series/LEU0252916100Q>

³³ Author-compiled HUD data

While these trends are generally positive regarding NOAH generation and preservation, it is important to note that these data include both homeowners and renters. Particularly given the variation in results by tenure and tenure transition via the repeat income measure, it follows that this measure should delineate results by housing tenure, which is outlined in the next subsection for both measures.

4.5.2 Filtering outcomes by tenure shifts nationally

When evaluating how outcomes vary based on tenure (and shifts in tenure), more trends emerge. Of the 32.7 million units represented within this analysis, about 17.8 million units ended as renter-occupied (i.e., “Renter-Renter” or “Owner-Renter” tenure shift) during this time frame. As shown in *Table 2* (p. 61), amongst units where occupants in the base year and final year are renters (“Renter-Renter”), the point estimate for overall logged change in income is negative, indicating that those renter only units are generally filtering downward, though the negative change is only significant at the 95% level for observations with only one turnover. However, these types of turnovers did net over 400,000 more units that filtered downward than upward, an estimated 51.3% of these units.

Estimates for units that were either occupied by a renter in the base or final year (“Renter involved”) show that more units have filtered downward than upward (i.e., more units had a decrease in logged change in income than units that had an increase in logged change in income). Overall, an estimated 50.06% of these units filtered downward during this time frame, though again the estimate that the majority of units filtered downward is not significant at the 95% level and the point estimate of change in repeat income was +4.6%.

For units that ended with a renter occupant (“Renter end”), point estimates indicate both a majority of units filtering downward (though not a statistically significant majority) and a

negative change in repeat income (which is also not statistically different from zero). Renter-end units saw 400,000 more units filter downward than upward, though other types of tenure shifts involving renters had a similarly higher number of units that filtered upward than downward. As a result, it would be most accurate to say that no significant filtering shifts (upward or downward) were observed for units that were renter-occupied during the 2015 to 2023 time period based on the repeat income measure.

On the other hand, when evaluating units that ended as owner-occupied, there are differing trends in filtering dynamics compared to units that ended as renter occupied. Of the 32.7 million units represented within this analysis, about 14.9 million units ended as owner-occupied (i.e., “Renter-Owner” or “Owner-Owner”) during this time frame. Both units that shifted from renter-occupied to owner-occupied (“Renter-Owner”) and those that remained owner-occupied (“Owner-Owner”), had overall increases in logged change in income for those units. As opposed to the renter units, these estimates were also statistically significant at the 95% level. Owner-owner units had substantially positive increases in logged change in income (+32.8%) during this time frame with only 47.0% of units filtering downward, resulting in over 750,000 more units filtering upward than downward. The appreciation in repeat incomes was even more pronounced for rental units that shifted to owner-occupancy (“Renter-Owner”). These units had an estimated growth of +65.3% in repeat income with only 42.0% of units filtering downward and nearly 390,000 more units filtering upward than downward.

Table 1: Summary statistics on filtering trends nationally, by turnover specification, repeat income measure

	Logged Five-Year Change in Income			
	Mean	SE	CI [lower]	CI [upper]
Total	0.1540	0.0289	0.0973	0.2107
Single TO	0.1781	0.0369	0.1057	0.2504
Multi TO	0.0854	0.0477	-0.0081	0.1788
	Filtering outcomes (total units)			
	Downward Filtered (DF)	SE	Upward Filtered (UF)	SE
Total	15,982,820	197,592	16,708,608	223,279
Single TO	11,756,007	177,925	12,461,483	210,930
Multi TO	4,226,813	108,777	4,247,126	112,958
	Logged Five-Year Change in Income			
	% DF	SE	% UF	SE
Total	48.88%	0.46%	51.10%	0.46%
Single TO	48.53%	0.59%	51.44%	0.60%
Multi TO	49.87%	0.92%	50.11%	0.92%

Table 2: Summary statistics on filtering trends nationally, by tenure shift type, repeat income measure

<i>All turnovers</i>					
Tenure Shift	Logged Change in Income	Weighted N	Downward filtered total	% Downward filtered	Net Downward Filtered
OO (owner, owner)	0.328	12,510,743	5,875,805	46.97%	-759,133
RO (renter, owner)	0.653	2,411,571	1,012,307	41.98%	-386,957
OR (owner, renter)	0.100	2,083,967	1,039,673	49.89%	-4,620
RR (renter, renter)	-0.054	15,693,105	8,055,035	51.33%	424,922
Renter end	-0.036	17,777,072	9,094,709	51.16%	420,302
Renter involved	0.046	20,188,643	10,107,016	50.06%	33,345
<i>Total (all shifts)</i>	0.154	32,699,386	15,982,820	48.88%	-725,788

<i>Single Turnover</i>					
Tenure Shift	Logged Change in Income	Weighted N	Downward filtered total	% Downward filtered	Net Downward Filtered
OO (owner, owner)	0.377	10,977,548	5,079,848	46.27%	-817,852
RO (renter, owner)	0.687	1,697,190	720,033	42.43%	-257,124
OR (owner, renter)	0.124	1,740,581	874,803	50.26%	9,026
RR (renter, renter)	-0.123	9,809,127	5,081,323	51.80%	360,475
Renter end	-0.086	11,549,708	5,956,126	51.57%	369,501
Renter involved	0.013	13,246,898	6,676,159	50.40%	112,377
<i>Total (all shifts)</i>	0.178	24,224,446	11,756,007	48.53%	-705,476

<i>Multiple Turnovers</i>					
Tenure Shift	Logged Change in Income	Weighted N	Downward filtered total	% Downward filtered	Net Downward Filtered
OO (owner, owner)	-0.025	1,533,195	795,957	51.91%	58,719
RO (renter, owner)	0.574	714,381	292,274	40.91%	-129,833
OR (owner, renter)	-0.023	343,386	164,870	48.01%	-13,646
RR (renter, renter)	0.061	5,883,978	2,973,712	50.54%	64,447
Renter end	0.056	6,227,364	3,138,582	50.40%	50,801
Renter involved	0.110	6,941,745	3,430,856	49.42%	-79,032
<i>Total (all shifts)</i>	0.085	8,474,940	4,226,813	49.87%	-20,312

As previously described, units are filtering upward in general with the overall estimated logged five-year change in incomes being +15.4% nationally with an estimated 0.7 million more units filtering upward than downward during this time frame. Based on the tenure shift tabulations, this upward filtering trend is driven by units that either were owner-occupied the entire time period or those that shifted to owner-occupancy during the study period. Importantly, tenure shifts themselves are also driving changes in logged income upward. An estimated 18.1 million units began as renter-occupied while there was an estimated 17.8 million renter-occupied units by the end of the study period.

Conversely, owner-occupied units started at 14.6 million and grew to 14.9 million during this time period. This net shift in tenure of roughly 300,000 units makes up a significant portion, but not majority, of the estimated upward filtering of 0.7 million units nationally during this time frame. However, owner-owner units do seem to be driving almost all of the upward filtering nationally with an estimated 0.8 million owner-owner units filtering upward during this time frame. Conversely, however, rental units are not downward filtering overall and, as a result, are not counterbalancing the trends observed amongst owner-occupied units.

When evaluating shifts in affordability by tenure using the gross rent threshold measure, the results have some differences. As shown in *Table 3* on the next page, the observations in the *Renter End* specification represent about 25.7 million units. Just under 58% (~14.9 million units) were Always Unaffordable while 16% (~4.1 million) were Always Affordable. Amongst these units slightly more filtered upward (~3.7 million) than downward (~3.1 million). This means that the NOAH rental housing stock contracted from 7.8 to 7.2 million units during the study period, representing a decrease of 7.7% in the NOAH rentals nationally.

However, the best way to understand the state of affordable market-rate rental housing is to look at both affordability and tenure shifts simultaneously. *Table 4* (p. 64) shows units in this panel that were either affordable in 2015 or in the last year of the analysis along with the tenure for both the base and final years. For units that were only owner-occupied, the number of units deemed affordable at the 50 percent of AMI threshold grew from 25.9 million in 2015 to 30.7 million during the study period. Units that were only renter-occupied saw an increase in affordable units, from 5.8 million in 2015 to 6.1 million in the final year. However, the last two lines in the table might be most telling—the number of units that were renter occupied in 2015 and affordable totaled 7.2 million in 2015, which is nearly equal to the number of units that ended as renter-occupied—an estimated increase of 23,000 affordable units in total. Specifically, renter to renter transitions generated about 330,000 additional affordable rental units during the study period while tenure shifts netted a loss of 300,000 affordable rental units, a 0.3% net increase in affordable rental units using this measure.

Table 3: Descriptive statistics on filtering outcomes nationally, gross rent threshold method³⁴

Filter type	All units		Renter End		Renter Involved	
	Units	% of total	Units	% of total	Units	% of total
<i>Always Affordable</i>	24,410,000	27.7%	4,117,000	16.0%	4,998,000	16.4%
<i>Always Unaffordable</i>	37,370,000	42.4%	14,850,000	57.8%	16,870,000	55.5%
<i>Downward Filtered</i>	15,630,000	17.7%	3,065,000	11.9%	4,369,000	14.4%
<i>Upward Filtered</i>	10,680,000	12.1%	3,668,000	14.3%	4,172,000	13.7%

³⁴ These data were approved for release by the US Census Bureau (CBDRB-FY26-P3221-R12982)

Table 4: Descriptive statistics on filtering outcomes nationally, by tenure, gross rent threshold method³⁵

<i>Transition type</i>	Affordable 2015	Affordable last year
Owner to Owner	25,920,000	30,670,000
Renter to Owner	1,385,000	2,186,000
Owner to Renter	2,011,000	1,078,000
Renter to Renter	5,774,000	6,104,000
Started Renter	7,159,000	
Ended Renter		7,182,000

4.5.3 Conclusions

When evaluating outcomes using the repeat income measure, market-rate housing units have generally been filtering upward from 2015 to 2023, though the magnitude and direction of filtering vary by types of tenure transitions. In general, units that were occupied by renters after their final turnover, have either lower estimates for increase in repeat incomes or negative estimates, though most of these estimates are not statistically different from zero. On the other hand, units that are owner occupied after the final turnover have had strong upward filtering estimates that are also generally statistically significant. Therefore, owner-occupied units are driving the trends upward filtering nationally using the repeat income.

In addition to variation in outcomes by tenure types, the units in the repeat income panel of AHS data experienced shifts in housing tenure during this time period. Specifically, about 300,000 housing units shifted from renter-occupied to owner-occupied during this time period. This shift amounts to a 1.75% decrease in units that were renter-occupied in the original 2015 sample and a 2.08% increase in units that were owner-occupied. These trends in the data align with national trends during the same period, with ACS data estimating a 2.19% drop in renter-occupied units and an increase of 8.99% owner-occupied units. This would seem to indicate that

³⁵ These data were approved for release by the US Census Bureau (CBDRB-FY26-P3221-R12982)

the panel's loss of renter-occupied units was driven at least in part by national shifts in tenure rather than renters simply being displaced by wealthier homeowners. Further evidence is found via the Federal Reserve, which estimates a shift in homeownership rate nationally from 63.7% in Q1 of 2015 to 66.0% in Q1 of 2023³⁶. This equates to a 3.6% growth in homeownership rates during that period.

Interestingly, ACS data also indicates that overall population growth (4.20%) was outpaced by the growth in housing units (6.73%) nationally during the study period. While the panel's owner-occupied growth was lower than these national averages, the loss of renter-occupied housing units still indicates that renters occupying these units may have been displaced by these aggregate shifts in housing tenure. ACS estimates indicate an overall decrease in renter population between 2015 (106.7 million) and 2023 (104.3 million), which paired with housing unit growth above population growth would seem to make the housing market more competitive amongst landlords and sellers. That said, growth in single family housing construction outpaced multifamily construction growth during this time period (Federal Reserve Bank of St. Louis, 2023) and—as described later in this chapter (see *Section 4.6*)—newer units are generally less likely to be affordable. Thus, the loss of older existing rental units to tenure shifts, despite growth in multifamily construction overall, could be impacting filtering outcomes for renters nationally during this study period.

When using the gross rent measure, the number of units that were affordable at the 50% of AMI threshold grew from 2015 to the end of the study period at first glance. Initially, 39.8% of all market-rate units were affordable in 2015 before that share grew to 45.5% by the end of the

³⁶ See <https://fred.stlouisfed.org/series/RHORUSQ156N>

study period. However, this panel of data included both renter- and owner-occupied units. After evaluating tenure and affordability shifts, it became clear that homeownership became more affordable relative to the 50% of AMI threshold during this time period, accounting for nearly all of 4.9 million units that filtered downward during this time. However, less than twenty-five thousand renter-occupied units filtered downward during this time.

The panel of data analyzed using the gross rent threshold method represented about 88.1 million units. Just under 7.2 million of these units were affordable rental units in the beginning year and that number remained just under 7.2 million in the final year. Overall, 8.1% of housing units in 2015 were affordable rental units before growing slightly to 8.2% of all units by the end of the study period. This seems to indicate that the number NOAH rental units during the study period remained fairly constant. This contrasts to some extent with the outcomes outlined in 4.5.2 from the repeat income method which estimated that the majority of units that ended as renter-occupied filtered downward (i.e., had final occupants whose incomes were lower than the initial occupant). Therefore, it could be said that while incoming renter households tend to have lower incomes than previous occupants, the number of units affordable at HUD's very low-income tier has gone relatively unchanged during this time period.

As mentioned previously, there are national-level housing tenure shifts that are shaping a lot of these results. The gross rent threshold method seems to further reveal that in addition to shifts in more owner-occupied units, homeownership seems to also be more affordable. This likely is related to near historic lows in mortgage interest rates after the global pandemic of 2020³⁷, which may have deepened disparities in housing affordability between tenants and

³⁷ See <https://www.freddiemac.com/pmms>

homeowners. This is likely less to do with new purchases during this time period, as interest rates impact home sale prices, but there is some evidence that homeowners benefited significantly from historic lows in interest rates during the COVID-19 pandemic, with typical borrowers who refinanced during this time seeing their monthly payments reduced by an average of \$279. Importantly, this refinancing activity also had embedded differences across ethno-racial groups with 12 percent of White borrowers refinancing during this time compared to only 6 percent of Black and 9 percent of Hispanic borrowers (Gerardi et al., 2021).

The following sections and chapters attempt to parse out some of the factors underlying these trends and outcomes, including how changes to local HUD FMRs are impacting the gross rent threshold measure in general. Additionally, further analyses will evaluate how household and housing unit characteristics impact outcomes and other sources of variation in filtering trends (e.g., housing market trends, unit age and quality, etc.).

4.6 How does filtering vary by unit age? Is this relationship linear?

A key part of the filtering process is unit aging and, to some extent, degradation that makes the unit less attractive to higher income households over time. Therefore, as units age, it is generally expected that they are more likely to be occupied by lower income households (Rosenthal, 2014). However, there have been instances where filtering slows amongst very old units, creating a “U”-shaped relationship between unit age and filtering where filtering slows at some point and reverses direction for older housing units that have either been rehabbed, are of higher quality (e.g., survivor bias), or for other reasons become more valuable over time.

In general, this “U” relationship has not been found in the U.S. though there is evidence of this phenomenon in other countries like Australia (Palm et al., 2020) and Canada (Skaburskis,

2006). However, the primary analyses showing a linear relationship between unit age and downward filtering in the U.S. included timeframes around the mortgage crisis of 2008 (Kim et al., 2013; Rosenthal, 2014). As a result, this relationship between unit age and filtering outcomes is worth evaluating further using the 2015 to 2023 AHS data panel.

The remainder of this section will evaluate how filtering varies across unit age bins nationally. First, some descriptive statistics on filtering outcomes by unit age will provide an initial overview of possible variation before a regression analysis will be done in order to understand whether unit age is a predictor of filtering outcomes when controlling for other important factors that impact filtering.

4.6.1 Filtering variation by unit age

To start, all units with one or more turnovers were sorted into 10-year bins by the age of the unit. This means that outcomes were delineated by units aged 0 to 9 years old, followed by 10 to 19 years, 20 to 29, and so forth. The AHS dataset stops specifying the year built for buildings that were built before 1919, so the final age bin is for units aged 100 to 109 years or older, as units built in 1919 would be 104 years of age in 2023, though some of these units may be older than 109 years. Both the constructed panels do include units added to the survey datasets after 2015 since 2015 weights were used for all analyses and therefore units without 2015 weights were excluded. As a result, the data for units in the newest age bin (0 to 9 years) was relatively limited, resulting in higher standard errors.

Table 5 (p. 70) shows the outcomes by age bin for both the overall change in logged five-year incomes and the percentage of units that have a negative change in logged incomes (i.e., percentage of units that have downward filtered). Numbers that are in bold indicate changes in

logged incomes that are statistically significant at the 95% level and where the percentage of units that filtered downward is statistically significant and above or below 50% (i.e., the majority of units filtered upward or downward).

The outcomes shown in this table reveal that in general unit age does not have a significant impact on filtering outcomes. The confidence intervals for newer units (built within the last 50 years) all indicate statistically insignificant differences from 0 for changes in repeat income and the confidence interval for the percent that filter downward largely range from 44 to 55 percent with point estimates largely falling between 45 and 52 percent.

However, units aged 50 years to 69 years have estimates that are statistically significant and positive, indicating that those units are generally filtering upward. This is also true of units aged 100 years or older. Similarly, a significant majority of units in the 60 to 69 and 100-to-109-year bins are filtering upward (i.e., less than 50% of units had negative changes in repeat incomes). While the other values are not statistically significant, they do show a general trend of changes in repeat income being highest around years 50 to 69 and tapering off on either side of that age range.

Table 6 (p. 70) shows the aggregate number of units by gross rent threshold filtering outcomes (i.e., Always Affordable - AA, Always Unaffordable - AU, Downward Filtered - DF, and Upward Filtered - UF) and Unit Age bin. Additionally, the table shows the percentage share of each outcome, by Unit Age Bin. Overall, these results seem to indicate that affordability is most prominent amongst units that are 40 years or older. While upward filtering is more prominent for older units, newer units are more likely to be Always Unaffordable.

Table 5: Filtering trends nationally by unit age, repeat income

<i>Unit Age Bin (Years)</i>	<i>5-Year Income Change</i>	<i>95% CI</i>	<i>% Filtered Downward</i>	<i>95% CI</i>
0 to 9	-0.288	(-1.045, 0.470)	0.562	(0.430, 0.692)
10 to 19	-0.103	(-0.374, 0.168)	0.508	(0.458, 0.557)
20 to 29	0.051	(-0.071, 0.174)	0.517	(0.494, 0.538)
30 to 39	0.048	(-0.099, 0.195)	0.499	(0.472, 0.525)
40 to 49	0.100	(-0.049, 0.250)	0.494	(0.470, 0.517)
50 to 59	0.265	(0.113, 0.416)	0.486	(0.462, 0.510)
60 to 69	0.309	(0.135, 0.483)	0.449	(0.421, 0.476)
70 to 79	0.182	(-0.007, 0.371)	0.470	(0.439, 0.500)
80 to 89	0.211	(-0.053, 0.476)	0.490	(0.448, 0.532)
90 to 99	0.259	(-0.145, 0.663)	0.502	(0.452, 0.552)
100 to 109	0.246	(0.072, 0.418)	0.470	(0.441, 0.499)

Table 6: Filtering trends nationally by unit age, gross rent threshold³⁸

<i>Unit Age</i>	<i>Filtering Outcomes, total units</i>				<i>Filtering Outcomes (% by Unit Age Bin)</i>			
	AU	AA	DF	UF	AU	AA	DF	UF
<i>0-9</i>	104,510	13,698	22,456	13,743	67.7%	8.9%	14.5%	8.9%
<i>10-19</i>	519,397	32,298	115,788	57,776	71.6%	4.5%	16.0%	8.0%
<i>20-29</i>	2,746,119	370,605	712,362	430,331	64.5%	8.7%	16.7%	10.1%
<i>30-39</i>	2,100,104	484,806	731,316	370,645	57.0%	13.1%	19.8%	10.1%
<i>40-49</i>	2,305,005	752,725	821,590	504,090	52.6%	17.2%	18.7%	11.5%
<i>50-59</i>	2,097,440	936,447	837,839	516,527	47.8%	21.3%	19.1%	11.8%
<i>60-69</i>	1,800,104	830,338	780,742	497,438	46.1%	21.2%	20.0%	12.7%
<i>70-79</i>	1,928,935	977,499	815,168	514,870	45.5%	23.1%	19.2%	12.2%
<i>80-89</i>	904,243	465,085	309,923	244,867	47.0%	24.2%	16.1%	12.7%
<i>90-99</i>	591,479	264,204	214,345	165,583	47.9%	21.4%	17.3%	13.4%
<i>100-109</i>	1,910,205	764,908	628,302	452,538	50.9%	20.4%	16.7%	12.0%

³⁸ These data were approved for release by the US Census Bureau (CBDRB-FY26-P3221-R12982)

In fact, for each of the age bins for units less than 30 years old, about 75 to 80 percent of all units are either Always Unaffordable or Upward Filtered. On the other hand, about 40 percent of units aged 50 to 89 years are either Always Affordable or Downward Filtered. As a result, this table offers a bit more context than *Table 5* because of the differences between the measures. For example, while older units do have higher rates of *Upward Filtering*, they also have increased shares of units that are *Always Affordable* and lower rates of units that are *Always Unaffordable*.

4.6.2 Regression analyses: repeat income

To better understand the relationship between unit age and filtering variation, changes in repeat income were regressed on unit age and several control variables. Notably, the previous table shows how repeat income changed without any controls for the incomes of the original occupants, CBSA-level fixed effects, and other important variables that impact the repeat income measure. Below is the base model used to assess this relationship for the repeat income measure:

$$Y = \beta_0 + \beta_1 \text{UnitAge}_{i,2023} + \beta_2 H_{i,t} + \beta_3 H_{i,t+n} + \beta_4 U_{i,t} + \alpha_{cbsa} + \varepsilon, \text{ where:}$$

$\text{UnitAge}_{i,2023}$ represents the age of the unit, i , in the year 2023, which is calculated as (2023 - Year Built);

$H_{i,t}$ represents a vector of household variables for the occupant of a given unit i in the base year t , including housing tenure, income quartile, and whether the householder is housing choice voucher holder;

$H_{i,t+n}$ represents a vector of household variables for the occupant of a given unit i in the year $t+n$, where n represents the number of years between the base year, t , and final turnover year. This includes whether the final year occupant was a voucher holder as well as whether the tenure of the occupant changed after the final turnover;

$U_{i,t}$ represents a vector of unit-level variables, which in this specification includes the variable “Gut Rehab” which indicates whether a gut rehab has been done on a given unit, i , during the study period and a variable indicating whether the unit was rent-controlled in the base year;

α_{cbsa} represents CBSA fixed effects; and,

ε represents the error term

The output of this model is shown in *Table 7* on the next page and includes variables like whether the beginning occupant was a renter (“*Renter (Base Year)*”), whether the unit shifted

tenure (e.g., a rental unit became owner-occupied), whether the initial or final occupants were voucher holders, whether the unit was subject to some form of rent control in the base year, and whether or not the unit had been rehabilitated during the panel period. *Unit age* is the variable of most interest here and it indicates that for every year a housing unit's age increases, the logged change in repeat incomes falls by 0.004. This is roughly equivalent to a 0.4% decrease in repeat real incomes per year the unit ages, a magnitude that is similar to results of recent research (Liu et al., 2021; Rosenthal, 2014).

As outlined in *section 4.5* of this chapter, tenure also impacts filtering outcomes substantially, as is evidenced by the Renter (Base Year) and Tenure change control variables. The base year income quartiles, which were included, are also important controls as lower income tiers are more likely to experience larger shifts in repeat incomes.

*Table 7: Regression output for base repeat income model with Unit Age*³⁹

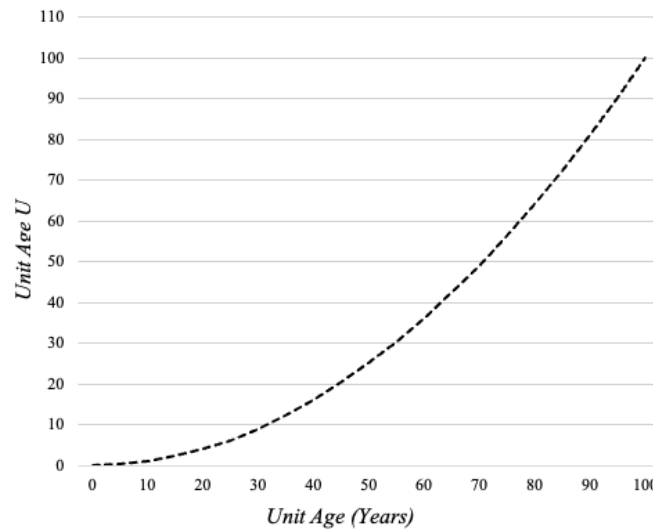
	<i>5-Year Income Change</i>	<i>se</i>	<i>p value</i>
Intercept	3.300	0.110	0.000
Unit Age	-0.004	0.001	0.000
Renter (Base Year)	-0.857	0.058	0.000
Tenure change	0.268	0.066	0.000
Voucher Holder (Base Year)	0.491	0.250	0.051
Voucher Holder (Final Year)	-1.911	0.204	0.000
Rent Controlled (Base Year)	-0.302	0.440	0.494
Gut Rehab	0.113	0.073	0.122

Since the table in the descriptive statistics also indicated that unit age may not be a purely linear relationship, another variable, *Unit Age U* was created to account for a possible “U” relationship for filtering outcomes. Specifically, this variable accounts for the fact that units may be filtering up after they age a certain amount due to rehabilitation or due to having other

³⁹ N = 17,386; Weighted N = 32,699,386

desirable characteristics (e.g., historic homes).

Figure 1: Relationship between Unit Age and Unit Age "U" variable



This variable⁴⁰ is calculated by squaring *Unit Age* and dividing that raw number by 100. This would make it such that the *Unit Age U* variable is exponentially greater for older versus newer units. For example, a 100-year-old unit has a *Unit Age U* value of 100 ($100^2/100 = 100$) whereas units aged 10 years would have a value of 1 ($10^2/100 = 1$). *Figure 1* shows how the value of this variable relates to unit age over time. The outcomes from this second specification are shown in *Table 8* on the next page.

⁴⁰ $Unit\ Age\ U = (Unit\ Age^2)/100$

Table 8: Unit age model specification with the variable “Unit Age U,” repeat income

	5-Year Income Change	se	p value
Intercept	3.615	0.136	0.000
Unit Age	-0.017	0.004	0.000
Unit Age U	0.011	0.003	0.001
Renter (Base Year)	-0.858	0.058	0.000
Tenure change	0.269	0.066	0.000
Voucher Holder (Base Year)	0.490	0.248	0.051
Voucher Holder (Final Year)	-1.904	0.205	0.000
Rent Controlled (Base Year)	-0.333	0.439	0.449
Gut Rehab	0.134	0.073	0.070

In this specification, the two-unit age variables reveal an interesting relationship. The *Unit Age* coefficient (-0.017) indicates that unit age actually has a greater magnitude of impact on downward filtering or a stronger negative impact on repeat incomes. However, the coefficient for *Unit Age U* is positive indicating that older units have higher repeat incomes. As described earlier, this variable ranges between 0 to about 120 but values grow exponentially after 10 years of age. As such, this generally means that filtering slows amongst older units, but it does not necessarily fully reverse direction in terms of the impacts of unit aging. For example, a 10-year-old unit’s impact from unit age would be $(-0.170 + 0.011)$ equal to a 14.7% decrease⁴¹ in repeat incomes whereas a 50-year-old unit’s impact from age would be $(-0.850 + 0.275)$ equal to a 43.7% decrease and a 100-year-old unit’s impact would be $(-1.70 + 1.10)$ equal to a 55.1% decrease. This would indicate that older units realize sharper decreases in repeat incomes all other things equal over time, but that relationship plateaus over time. This seems to correspond to the descriptive statistics in Table 5. After adding controls and CBSA fixed effects, the second model specification shows that, at least in the earlier years of a unit’s life, the impact from units

⁴¹ $\text{Exp}(-0.17+0.011) = 0.853$, or a five-year repeat income that is 14.7% lower than the initial occupant

aging may be more pronounced than appeared initially.

4.6.3 Regression analyses: gross rent threshold

Using the gross rent threshold measure, whether a unit was affordable about the 50% of AMI level (a binary variable) was regressed on unit age and several control variables. Notably, the previous table shows how filtering outcomes varied without any controls for the initial rent levels, CBSA-level fixed effects, and other important variables that impact the gross rent threshold measure. Below is the base model used to assess this relationship:

$$Y = \beta_0 + \beta_1 \text{UnitAge}_{i,2023} + \beta_2 H_{i,t} + \beta_3 H_{i,t+n} + \beta_4 U_{i,t} + \alpha_{cbsa} + y_{i,t}, \text{ where:}$$

$Y = \text{AffordableUnit_last}$, a binomial outcome variable that indicates whether a unit is affordable in its last year of the study at the 50% of AMI level (1) or not (0). Affordable units include both downward filtered and always affordable units whereas unaffordable units include both upward filtered and always unaffordable units;

$\text{UnitAge}_{i,2023}$ represents the age of the unit, i , in the year 2023, which is calculated as (2023 - Year Built);

$H_{i,t}$ represents a vector of household variables for the occupant of a given unit i in the base year t , including housing tenure and whether the householder is housing choice voucher holder;

$H_{i,t+n}$ represents a vector of household variables for the occupant of a given unit i in the year $t+n$, where n represents the number of years between the base year, t , and final year with necessary data. This includes whether the final year occupant was a voucher holder as well as whether the tenure of the occupant changed after the final turnover;

$U_{i,t}$ represents a vector of unit-level variables, which in this specification includes the variable “Max Rehab” which indicates whether a gut rehab has been done on a given unit, i , during the study period and a variable indicating whether the unit was rent-controlled in the base year;

α_{cbsa} represents CBSA fixed effects;

$y_{i,t}$ represents time fixed effects, specifically the final year t of data for a given unit i ; and,

ε represents the error term

Table 9 on the next page shows the outputs, expressed as odds ratios, for a binomial logistic regression that predicts the impact of Unit Age on the likelihood a unit becomes affordable at the 50 percent of AMI threshold. In this initial specification, the outcomes on the surface seem to closely resemble the outputs generated by the repeat income method—though in

this table higher odds ratios indicate increased probability of a unit being affordable whereas the outputs in *Tables 7 and 8* indicate how variables relate to changes in income over time, meaning lower or negative changes in repeat incomes are associated with increased affordability. The main exception to this is the *Max Rehab* variable which in this output results in increased odds of a unit being affordable in the final year.

Table 9: Initial Unit Age specification, gross rent method

	<i>Estimate</i>	<i>se</i>	<i>p value</i>
Intercept	-0.854	0.089	0.000
Unit Age	0.004	0.001	0.000
Rent Control (base year)	0.398	0.150	0.009
Renter (base year)	-0.876	0.041	0.000
Tenure shift	-0.117	0.060	0.052
Voucher Holder (base year)	-0.297	0.137	0.031
Voucher Holder (last year)	1.180	0.146	0.000
MaxRehab	0.068	0.036	0.064
Affordable Unit (base year)	1.220	0.038	0.000

The variable of interest, *Unit Age*, indicates that for each year older a given unit is, the odds of it being affordable in the final year increases by 0.4%. The repeat income method output, using a similar model specification, associated an additional year of age as 0.4% decrease in repeat income. Though the U-Shape relationship between age and filtering outcomes for the gross rent method is less evident than the one observed using the repeat income method, the similar outputs in the base models warrant investigating this U-Shape relationship utilizing the gross rent method as well. *Table 10* on the following page shows this specification of the gross rent threshold method.

Table 10: *Unit Age U specification, gross rent method*

	<i>Estimate</i>	<i>se</i>	<i>p value</i>
Intercept	-1.378	0.111	0.000
Unit Age	0.025	0.003	0.000
Unit Age U	-0.018	0.003	0.000
Rent Control (base year)	0.447	0.152	0.004
Renter (base year)	-0.870	0.041	0.000
Tenure shift	-0.113	0.060	0.061
Voucher Holder (base year)	-0.299	0.137	0.031
Voucher Holder (last year)	1.191	0.147	0.000
MaxRehab	0.041	0.036	0.254
Affordable Unit (base year)	1.206	0.038	0.000

In this specification, *Unit Age* has a much more prominent impact and *Unit Age U* is also significantly impacting outcomes. Specifically, *Unit Age* in this specification indicates that for every year older a housing unit is aged, its likelihood of being affordable in the last year of the panel increases by 2.5%. While the impacts from *Unit Age U* do offset the linear age relationship, the impacts of *Unit Age U* are far lower magnitude than *Unit Age* in the first several decades. For example, a housing unit that is 50 years old is associated with $50^2/100$ (or 25) x -0.018, equaling -0.45, plus 50×0.025 (or 1.25), equaling a total of 0.8 log-odds. This would equal a 2.226 odds ratio, indicating that a 50-year-old housing unit is more than twice as likely to be an affordable unit than a new housing unit. A 100-year-old unit, on the other hand, would equate⁴² to a 2.014 odds ratio or just over twice as likely to be affordable as a new unit.

Since the *Unit Age U* is normalized by dividing values by 100, the coefficients imply that around the likelihood of a unit being affordable at the end of the panel increases from year 0 through year 69. This is interesting because the descriptive statistics in *Tables 5 and 6* showing filtering outcomes by age bin do not really delineate a big shift before/after this unit age range,

⁴² $(100 \times -0.018) + (100 \times 0.025) = 0.7$; $\exp(0.7) = 2.014$

though those outcomes are presented without any controls. As a result, these outputs would seem to indicate that downward filtering accelerates for the first nearly 70 years of a unit's life before tapering off thereafter. However, very old units are still far more likely to be affordable than new housing units, even considering this non-linear relationship.

4.6.4 Conclusions

In general, these data seem to indicate that, when controlling for baseline renter and unit characteristics, downward filtering generally accelerates as units get older nationally, though at a relatively modest pace with repeat incomes decreasing by 0.4% to 1.7% and the likelihood of units being affordable increase by 0.4% to 2.5% per additional year of age for a given unit. This generally follows what was shown in the descriptive data—older housing units tend to be more affordable compared to newer housing units.

However, the descriptive data showed that upward filtering also accelerates amongst older units. The Unit Age U variable was significant when included in the model, indicating that age and downward filtering have a non-linear relationship. Specifically, this variable has a higher value in later years, and the results indicate that filtering slows in the latter age ranges of housing units. While filtering outcomes do not reverse amongst very old units, downward filtering does plateau over time. Additionally, descriptive data shows that rehabilitations of units are systematically different between owner-occupied and rental units with 40% of owner-occupied units having rehabilitations compared to 5% of renter-occupied units that are greater than 50 years⁴³. However, when an interaction term for rental units and max rehab was included, the U

⁴³ Since the AHS relies on survey responses from occupants, part of this discrepancy could be driven from renters being unaware of whether renovations had taken place in recent years.

relationship still remained significant and of similar magnitude, indicating that even independent of upgrades, downward filtering slows down over time.

These outcomes generally align with previous findings from other studies (Liu et al., 2022) and the “U-shape” relationship between housing age and filtering rates could be driven by “survival bias” where higher quality units are more likely to remain in the housing stock for longer. This could possibly bias the repeat income measure for older units due to systemic differences in the quality of those units. This possibility is somewhat supported by the fact that the control for gut rehabilitations was insignificant, though it did have a positive point estimate. This could indicate that while gut rehabilitations might at times improve the value of a given housing unit and induce upward filtering, the housing units that survive to older ages may be simply of higher quality independent of physical alterations made to them. The conclusions section of this chapter (4.7.4) provides some details on how certain unit characteristics relate to the likelihood a unit is removed from the housing stock, providing some context on how units that are removed might differ from those that remain active over time.

While rehabilitations may not be the driving force of the upward filtering of older housing units, the role of a unit’s degradation may still partially explain downward filtering. It could be argued that unit age is a proxy for unit quality and that filtering is generally a process of degrading unit quality that subsequently makes the unit more affordable. As such, the next section of this chapter examines the relationship between housing quality and downward filtering rates.

While it was only included as a control, it is worth mentioning that the presence of a rent control policy in 2015 made it 56.4% more likely that a unit would be affordable in the last year of the study period using the gross rent threshold model. For the most part, however, both

measures show similar impacts for both their controls and independent variables. While the gross rent method is measuring affordability based on housing costs relative to HUD thresholds, base year income quartiles are still statistically significant at the $p < 0.05$ or $p < 0.10$ levels for each specification, even with a control for whether the unit was affordable in the base year. While expected, this provides further evidence of housing sub-markets, as units occupied by high income households are unlikely to downward filter below the 50% of AMI threshold.

Importantly, there also seems to be some evidence that homeowners are much more likely to have housing costs that are below the 50% of AMI threshold. While the descriptive statistics in *Section 4.5* showed that affordable rental units grew in general during the study period, units that were renter-occupied in 2015 were generally less likely to be affordable in the final year compared to owner-occupied units. As previously mentioned, shifting macro trends around housing tenure and mortgage rates (and refinancing) during this time period are likely shaping these outcomes.

4.7 Do units that have filtered downward have adequacy issues? How does inadequacy/unit quality impact filtering rates?

Particularly for NOAH, maintenance costs can outweigh potential revenue in certain cases (Garboden & Newman, 2012) and lower quality housing sub-markets could face higher vacancy rates or even abandonment as part of the filtering process (Galster, 1996, 2001; Mast, 2023). Additionally, there is some evidence that inadequacy and affordability are related at the city-level (Hipp et al., 2025). As a result, I hypothesize that older units, particularly those with inadequacy issues, are more likely to filter downward and possibly even be demolished.

First, I will show descriptive data on how filtering dynamics vary overall by adequacy, a created binary variable where 1 identifies units deemed moderately or severely inadequate. Second, I will include the adequacy variable in the equation utilized in the 4.2 regression analyses. I will include the inadequacy dummy variable (0=no inadequacy issues; 1=moderately or severely inadequate) in addition to the household base year characteristics, unit characteristics, and unit age variables outlined in 4.5 and 4.6.

4.7.1 Unit Age and Inadequacy

To start, the data were sorted into 10-year bins by the age of the unit as of 2023, the last survey year in the longitudinal panel. This means that outcomes were delineated by units aged 0 to 9 years old, followed by 10 to 19 years, 20 to 29, and so forth. As mentioned previously, the AHS dataset stops specifying year built for buildings that were built before 1919, so the final age bin is for units aged 100 to 109 years or older, as units built in 1919 would be 104 years of age in 2023.

Table 11 on the next page shows the outcomes by age bin for the percentage of units that have adequacy issues. These units are identified by top coding a HUD measure that determines

whether units are adequate (coded 1), moderately inadequate (coded 2), or severely inadequate (coded 3) based on HUD’s housing quality definitions. Severe issues include lack of plumbing or available toilets, exposed wiring, etc., or have five plus issues that are of lower severity (water leaks, rat sightings, holes in the floor, etc.). Moderately inadequate units have three to four issues that are of lower severity. For this study, units are designated as inadequate if they receive either a moderate or severely inadequate distinction via this HUD measure⁴⁴ (i.e., units are top coded as “Inadequate” if they are moderately or severely inadequate⁴⁵).

Table 11: Percentage of units that are moderately or severely inadequate by age bin

<i>Unit Age Bin</i>	<i>Repeat Income</i>		<i>Gross Rent Threshold</i>	
	<i>All</i>	<i>Renter-end</i>	<i>All</i>	<i>Renter-end</i>
<i>0-9</i>	4.9%	10.0%	4.8%	20.5%
<i>10-19</i>	1.0%	1.3%	3.1%	5.5%
<i>20-29</i>	3.2%	5.0%	2.6%	5.8%
<i>30-39</i>	3.3%	4.9%	3.5%	7.0%
<i>40-49</i>	4.8%	6.2%	4.3%	7.9%
<i>50-59</i>	4.4%	6.2%	3.9%	6.6%
<i>60-69</i>	6.6%	7.6%	4.6%	8.0%
<i>70-79</i>	5.0%	7.0%	4.8%	8.6%
<i>80-89</i>	6.6%	7.4%	7.3%	10.7%
<i>90-99</i>	7.6%	8.5%	10.4%	14.5%
<i>100-109</i>	8.8%	10.0%	7.5%	10.1%

In general, units do indeed have increasingly higher levels of inadequacy as they age. This relationship aligns with the general theory behind filtering and may imply that as units age, inadequacy issues increase and the value (and affordability) shifts in response. The only outlier to this otherwise linear relationship between age and adequacy, is the first age bin, which shows high inadequacy issues—though this age bin has very few observations since only units built in

⁴⁴ See https://www.huduser.gov/portal/publications/pdf/AHS_hsg_adequacy.pdf for detailed description of these measures

⁴⁵ A sensitivity analysis showed that this variable was not sensitive to the inclusion of moderately inadequate units. About 1.2% of units from the PUF-derived gross rent threshold sample are moderately inadequate and another 3.0% are severely inadequate.

2014 or later would be in that bin and this panel started with observations from 2015 on.

However, the descriptive data show that about 1 to 3% of units, depending on the sample used, aged 10 to 19 years have inadequacy issues and that proportion grows to about 7.5 to 9% of units aged 100 plus years in age. This table also does show that inadequacy issues are more prevalent amongst renter-occupied units amongst both samples.

In general, the percentage of units identified as inadequate increases by 0 to 2% every 10 years (i.e., each age bin), though those increases seem to generally plateau for units aged between 50 to 79 years before similar increases resume after that age range. This mostly mirrors the filtering variation by age range described in *section 4.6* and may be driven by the fact that severely inadequate units may be demolished or otherwise removed from the housing stock around this age range (e.g., survivor bias). However, while inadequacy and age do seem linked here, it is worthwhile to explore whether age is simply driving inadequacy or if inadequacy drives filtering variation independent of unit age.

4.7.2 Regression analyses: repeat income

To better understand the relationship between inadequacy, unit age, and filtering variation, changes in repeat income were regressed on unit age and several control variables. Notably, *Table 11* shows how unit adequacy varied by unit age without any controls, CBSA-level fixed effects, and other important variables that impact the repeat income measure. Below is the first specification used to assess this relationship, which builds on the base model by adding the inadequate variable. *Table 12* on the next page shows the outputs from this first specification.

$$Y = \beta_0 + \beta_1 \text{Inadequate}_{i,t+n} + \beta_2 H_{i,t} + \beta_3 H_{i,t+n} + \beta_4 U_{i,t} + \alpha_{cbsa} + \varepsilon, \text{ where:}$$

$\text{Inadequate}_{i,t+n}$ represents the whether the unit, i , in the final year, $t+n$, is top coded as Inadequate (moderately or severely inadequate = 1, adequate = 0).

Table 12: Inadequacy specification, repeat income method

	<i>Estimate</i>	<i>se</i>	<i>p value</i>
Intercept	3.686	0.136	0.000
Inadequate (last year)	-0.589	0.135	0.000
Unit Age	-0.016	0.004	0.000
Unit Age U	0.011	0.003	0.001
Renter (base year)	-0.931	0.060	0.000
Renter (base year)*MaxRehab	0.923	0.166	0.000
MaxRehab	-0.041	0.084	0.629

Notably, the intercept as well as the control variables had similar estimates and remained significant at the $p < 0.05$ level, including those no longer displayed on the table (e.g., voucher status). Both the magnitude and direction of the variable of interest, *Inadequate (last year)*, is worth noting—units with adequacy issues are more likely to filter downward and at a magnitude far greater than a unit aging. In fact, the point estimates would indicate that inadequacy issues would have a similar impact to downward filtering as a unit that has aged 50 years or more. Thus, inadequacy issues appear to be a strong driver of downward filtering that is more impactful than aging for the first 50 years of a unit’s lifecycle and similar to the impacts of a unit being 50 to 100 years old.

Another important outcome is the Renter (base year) and MaxRehab interaction term. This interaction term looks at how gut rehabs incrementally impact units that were initially renter-occupied, and the magnitude of the estimate is large and positive, indicating that rehabs of these units induce upward filtering, all other things being equal. In fact, the upward impact of a rental unit being rehabbed is stronger in magnitude than the downward impact of that same unit having inadequacy issues.

The AHS also has measures for neighborhood and unit quality based on respondent assessments. Specifically, there is a neighborhood measure and unit measure where respondents quantify on a 10-point scale what they would rate their unit and neighborhood (1 being the lowest and 10 being the highest). While unit quality is already captured via the “Inadequate (Final Year)” variable, it may be the case that neighborhood features are driving downward filtering more so than unit degradation.

Somerville and Holmes (2001) found that individual characteristics can impact whether a unit is demolished or removed from the housing stock but do not greatly impact affordability. Instead, they find neighborhood quality being the primary driver of changes to affordability. Given this prior finding, these initial results require further investigation. To address the role of neighborhood impacts, another specification included a variable “*Low Neighborhood Rating (Base Year)*” which indicates a bottom-coded score of 6 or lower in the AHS neighborhood quality measure. While a score of 6 may seem high, nearly 85 percent of the sample’s observations (14,661 of 17,386) received scores of 7 or higher⁴⁶. Thus, this variable is focused on roughly the lowest 15% of units in the sample. The results from this specification are shown in *Table 13* on the next page.

⁴⁶ A sensitivity analysis showed that this variable was not sensitive to this cut point. While magnitude of impact varied depending on the exact cut point, the collapsed binary variable remained significant for cut points of both 6 and 8.

Table 13: Inadequacy specification with neighborhood rating control, repeat income⁴⁷

	PUF sample		IUF sample	
	<i>Estimate</i>	<i>p value</i>	<i>Estimate</i>	<i>p value</i>
Intercept	3.649	0.000	3.265	0.000
Low Neighborhood Rating (base year)	-0.228	0.004	-0.149	0.051
Inadequate (last year)	-0.562	0.000	-0.503	0.001
Unit Age	-0.014	0.001	-0.013	0.003
Unit Age U	0.010	0.005	0.008	0.021
Rent Control (base year)	-0.294	0.505	-0.315	0.482
Renter (base year)*MaxRehab	0.918	0.000		
MaxRehab	-0.044	0.606	0.110	0.152
Tenure shift	0.129	0.073	0.212	0.004

These initial results show that the significance and magnitude of the inadequacy variable continue to hold, even when factoring in the neighborhood rating variable. That being said, a low neighborhood rating is also associated with a significant change in repeat incomes and is associated with a relatively strong downward shift in repeat incomes. This indicates somewhat mixed results when compared to those presented by Sommerville and Holmes (2001), particularly that unit quality seems to impact filtering incomes even when accounting for neighborhood quality. In fact, in specifications with impacts quantified for units that end as renter-occupied, there was not a significant impact on repeat incomes from low neighborhood ratings, meaning neighborhood quality seems to be impacting owner-occupied units but not renter-occupied units. Gut rehabs and changes in tenure were both associated with upward swings in repeat incomes, with rehabs particularly impacting units that were renter-occupied in the base year. Generally, this all makes intuitive sense—units that are rehabbed and perhaps even experience a shift in tenure are more likely to be occupied by households with higher incomes

⁴⁷ These IUF data were approved for release by the US Census Bureau (CBDRB-FY26-P3221-R13043); the overall sample of the IUF and PUF for these analyses are the same, but the IUF sample includes fixed effects for Metro (vs non-Metro) geographies in addition to CBSA and Census Division fixed effects

while units in lower quality neighborhoods or with adequacy issues are more likely to be occupied by lower-income households.

Importantly, these data do not account for neighborhood *change*, as the low neighborhood rating only identifies a low neighborhood score at one end of the paired measure (the base year). Further investigation into the relationship between neighborhood change and filtering dynamics will be investigated in *Section 5.8*, which evaluates filtering variation as it relates to gentrification.

4.7.3 Regression analyses: gross rent threshold

The sample for the gross rent threshold method had a similar distribution of inadequacy issues by unit age range as those in the repeat income method, as shown previously in *Table 11*. Namely, the inadequacy rate generally increases the older housing units are and the oldest housing units have uniquely high inadequacy rates.

Following the same reasoning as outlined in *section 4.7.1*, the following outputs assess how inadequacy issues might impact filtering outcomes. Specifically, this is meant to further investigate the extent to which unit age alone versus unit quality is impacting filtering outcomes. As such, the initial specification will use the same variables as used in *section 4.6.3* with the addition of the Inadequacy variable described in *section 4.7.1* for the repeat income regressions. Below is the formula used for this specification and *Table 14* shows the output from this model.

$$Y = \beta_0 + \beta_1 Inadequate_{i,t+n} + \beta_2 H_{i,t} + \beta_3 H_{i,t+n} + \beta_4 U_{i,t} + \alpha_{cbsa} + y_{i,t}, \text{ where:}$$
*Inadequate*_{*i,t+n*} represents the whether the unit, *i*, in the final year, *t+n*, is top coded as Inadequate (moderately or severely inadequate = 1, adequate = 0)

Table 14 (p. 90) shows that inadequacy does seem to impact affordability outcomes, though it is only significant at the $p < 0.10$ level for both the specifications—all observations and

those that ended as renter-occupied. The point estimate indicates that units with adequacy issues are roughly 14% more likely to be affordable at the end of the study period than similar units without adequacy issues. For renter-end units, the magnitude of impact from inadequacy is even greater while unit age impacts are not significant for these units. The gut rehab variable, *MaxRehab*, does not have a statistically significant impact on affordability in either specification. Overall, it seems that affordability in renter-occupied units is more prominently impacted by unit quality (issues) than owner-occupied units while unit age is more closely related to affordability in owner-occupied units.

Similar to the outcomes found using the repeat income method, these results seem a bit confusing on the surface. The oldest units in this longitudinal dataset have the most pervasive inadequacy issues and inadequacy is associated with increased likelihood of being affordable. However, filtering is estimated to taper off amongst these same units—those aged 70 years or older in particular. As a result, this method will also include a specification with a variable capturing neighborhood quality, specifically the same bottom-coded variable meant to indicate low-rated neighborhoods, *Low Neighborhood Rating (base year)*, that was used in the repeat income models. The outputs from this specification are shown on *Table 15* (p. 90).

Interestingly, the outputs from this measure and specification show that neighborhood characteristics (i.e., a low neighborhood rating) are slightly more important than unit quality (i.e., inadequacy) for units in general. This conflicts with what was observed utilizing the repeat income method where both unit inadequacy and neighborhood rating impacted filtering outcomes, with inadequacy having the larger magnitude of impact. However, in the renter-end specification, inadequacy and low neighborhood quality have similar magnitudes of impact on affordability.

Given that the relative importance of neighborhood rating versus inadequacy flips between the two specifications, the implication is that inadequacy impacts renter-occupied units more prominently relative to neighborhood quality while the reverse is true for owner-occupied units. However, both variables are more impactful for rental units than they are on owner-occupied units, which are more sensitive to age impacts. Considering this is evaluating changes in rent levels (relative to HUD-specified rents) whereas repeat income is evaluating changes in real incomes, it may be that prices set by landlords (i.e., rents) are more sensitive to neighborhood characteristics and trends whereas prices that higher income renters and potential homeowners are willing pay might be impacted by both neighborhood and housing quality, though more prominently by housing quality.

Table 14: Inadequacy specification, gross rent method⁴⁸

	<i>All observations</i>			<i>Renter-end</i>		
	<i>Estimate</i>	<i>se</i>	<i>p value</i>	<i>Estimate</i>	<i>se</i>	<i>p value</i>
Intercept	-1.379	0.111	0.000	-2.194	0.238	0.000
Inadequate (last year)	0.136	0.081	0.096	0.213	0.112	0.060
Unit Age	0.025	0.003	0.000	0.009	0.006	0.143
Unit Age U	-0.018	0.003	0.000	-0.003	0.005	0.595
Rent Control (base year)	0.446	0.153	0.004	0.316	0.165	0.058
MaxRehab	0.043	0.036	0.242	0.180	0.255	0.481

Table 15: Inadequacy specification with Low Neighborhood Rating, gross rent method⁴⁹

	<i>All observations</i>			<i>Renter-end</i>		
	<i>Estimate</i>	<i>se</i>	<i>p value</i>	<i>Estimate</i>	<i>se</i>	<i>p value</i>
Intercept	-1.392	0.110	0.000	-2.190	0.250	0.000
Inadequate (last year)	0.121	0.083	0.144	0.237	0.111	0.034
Low Neighborhood Rating (base year)	0.161	0.049	0.001	0.218	0.086	0.013
Unit Age	0.024	0.003	0.000	0.008	0.006	0.187
Unit Age U	-0.017	0.003	0.000	-0.002	0.005	0.674
Rent Control (base year)	0.448	0.153	0.004	0.311	0.162	0.057
MaxRehab	0.040	0.038	0.294	0.125	0.267	0.640

⁴⁸ These data were approved for release by the US Census Bureau (CBDRB-FY26-P3221-R13043)

⁴⁹ These data were approved for release by the US Census Bureau (CBDRB-FY26-P3221-R13043)

4.7.4 Conclusions

The data indicates that older housing units in the AHS sample do tend to have higher rates of inadequacy, though the percentage of units that are inadequate does plateau for units aged 40 to 70 years before again increasing thereafter. While theories about “survivor bias,” the idea that higher quality units are more likely to remain in the housing stock, indicate that those units should be more likely to upward filter, older units actually have higher rates of inadequacy which would normally be associated with higher rates of filtering. This is interesting because, as *Section 4.6* indicates, downward filtering generally stalls after units age beyond 50 years or so. These theories could still hold, however, as it may be a specific subgroup of older units that have persistent inadequacy issues while others may be of much different quality (and cost).

After looking at the descriptive statistics, a regression analysis with controls from the prior sections of this chapter included was run. These controls included *Unit Age* and *Unit Age “U”*, and the results indicate that even with prior relationships between unit age, tenure, and rent control and repeat income changes holding consistent, inadequacy still had a significant impact on repeat income. Specifically, units with adequacy issues have stronger downward shifts in repeat income compared to units that do not have adequacy issues. The impacts of inadequacy issues also remained when controlling for neighborhood quality, meaning even in high-quality neighborhoods that units with inadequacy are more likely to filter downward than units without adequacy issues.

In fact, the magnitude of impact from inadequacy (-0.562) on repeat incomes actually is greater than the impact from being in a neighborhood with a low rating (-0.228). This could imply that units with inadequacy issues in average or good neighborhoods would be more likely

to filter downward than units without inadequacy issues in neighborhoods with a low rating. This would to some extent run contradictory to prior findings by Sommerville and Holmes (2001) that indicated that neighborhood-level and city-level indicators were bigger determinants of filtering outcomes than unit-characteristics, though their same city- and neighborhood-level indicators were not included in these specifications.

The gross rent threshold method yielded similar results, with both *Unit Age* and *Unit Age U* significantly impacting filtering outcomes over time for units in general. The specification with only inadequacy included also indicated that unit quality was impacting filtering outcomes. However, this measure differed from the repeat income measure when neighborhood rating was also included alongside inadequacy. For renter-end units, these impacts were even more prominent, with inadequacy actually having a more prominent impact than a low neighborhood rating. Interestingly, for both this model and the repeat income model, gut rehab did not have a significant impact on filtering outcomes with these variables included in the model though an interaction term in the repeat income model indicates that rehabilitations do significantly impact affordability outcomes for renters. As mentioned previously, these analyses do not include other important city- and neighborhood-level characteristics that could be impacting outcomes, but analyses in *Chapter 5* and *Chapter 6* will include such variables in their specifications in order to further evaluate this relationship.

In addition to the outlined analyses, I also used a “removed” outcome variable to assess how unit characteristics are impacting the likelihood of the unit being removed from the available housing stock. Removal includes but is not limited to units that are demolished—this variable is based on the AHS’s “Type C” designation which includes units lost to demolition, disaster loss, to structural conversion, and other situations where the unit no longer exists in the

same form or physical location⁵⁰. *Table 16* below shows how demolitions and removals relate to the two measures used. For the gross rent threshold method, it seems that units that started as affordable were more likely to eventually be removed from the housing stock in general and be demolished specifically. In terms of outcomes from the repeat income sample, units that eventually were removed actually had higher estimates of increases to repeat incomes than those that were not removed. However, demolished units had a negative point estimate for repeat incomes, indicating that those units had more prominent downward filtering before being demolished, though due to the small sample size the standard error is quite high, and the outcome is not statistically different from zero.

Table 16: Removal and demolition descriptive statistics by measure

Affordable Unit (BY)	% Demolished	% Removed
<i>No</i>	0.21%	1.39%
<i>Yes</i>	0.37%	2.40%

<i>Removal Classification</i>	<i>Repeat Income</i>	<i>se</i>
Not removed	0.151	0.029
Removed (all)	0.487	0.234
Demolished	-0.141	0.486

Table 17 (p. 94) shows how key variables relate to the likelihood a unit is removed from the housing stock after being regressed on the “removed” variable. Coefficients are broken out by sample since different samples are used for each measure, but the outcomes are fairly consistent in terms of direction and significance. Specifically, units that are initially occupied by renters and those that have inadequacy issues in the final year of the panel are more vulnerable to

⁵⁰ https://www.census.gov/programs-surveys/ahs/tech-documentation/help-guides/2015-later/national-sample-case-history_2015.html provides detailed descriptions of Type C reasons for noninterview.

being removed from the housing stock. Similarly, units that are affordable at the 50% of AMI threshold are also more likely to eventually be removed. While only significant in the Repeat Income sample, the presence of a voucher holder in the final year has a negative point estimate for both samples, indicating that units that otherwise might be vulnerable to removal are more likely to remain if their occupant is a voucher holder.

Table 17: Removal regression outputs by measure

Variable	Coefficient Value, by sample	
	<i>Repeat Income</i>	<i>Gross Rent</i>
Renter (Base Year)	0.009***	0.528***
Voucher Holder (Final Year)	-0.019*	-0.112
Affordable Unit (Base Year)	NA	0.470**
Inadequate (Final Year)	0.034**	0.686***
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$		

4.8 Discussion

In this Chapter, an overview of nationwide filtering trends for market-rate housing units from 2015 to 2023 was provided. This examination involved quantifying the magnitude and direction of filtering trends conditional on various characteristics associated with stronger or weaker filtering trends. Both theory and quantitative results from prior research informed these initial analyses, with some interesting results.

The first finding is that in general market-rate units are not filtering downward nationally from 2015 to 2023 with a 16.6%⁵¹ increase in repeat incomes increasing nationally and an estimated 48.9% of units filtering downward. This aligns with the findings from Spader (2024) that filtering has slowed down during the time frame of this most recent panel of AHS data. As outlined in 4.5.2, some of these trends are likely driven by shifts in housing tenure nationally. Outputs show that owner-occupied units and tenure shifts are associated with higher repeat incomes, so the overall filtering measures are likely sensitive to national shifts in housing tenure. However, the gross rent threshold measure showed overall changes in affordable rental units being relatively flat, with 7.16 million units being affordable in the base year compared to 7.19 million affordable units in the final year.

As with the repeat income measure, units that started and ended as renter-occupied showed evidence of downward filtering, with about 330,000 of these units filtering downward over the study period. For units that ended as renter-occupied, about 600,000 more units filtered upward than downward, indicating that renters were more likely to occupy units that filtered upward than those that filtered downward. These outcomes largely align with the first two hypotheses outlined in 4.4—while repeat incomes were growing in general (indicating upward

⁵¹ Projected 5-year growth rate

filtering in general) they were also negative overall for renter-to-renter turnovers (indicating downward filtering for renters) whereas the gross rent measure showed more rental units filtering upward than downward overall.

In *section 4.6*, the relationship between unit age and filtering was examined. Initial descriptive statistics did not seem to indicate a linear relationship between age and filtering, with both newer and very old units showing more downward filtering than units aged 50 to 70 years of age, which were generally filtering upward. The initial regression specification actually showed that Unit Age had a statistically significant impact on repeat incomes that was roughly equivalent to 0.4% decrease per year, lower than the estimated downward filter rates observed for both owner- and renter-occupied units by Rosenthal (2014). However, there are shifting trends around the 50-to-70-year age range for housing units, so the *Unit Age U*⁵² variable was created to see if filtering trends were non-linear and whether downward filtering slowed amongst older units.

The resulting analyses that included the variable *Unit Age U* produced evidence that filtering trends were nonlinear, and filtering rates slowed amongst older units. With this variable included the magnitude of impact from *Unit Age* also ticked up in both the repeat income and gross rent models. In both models the *Unit Age U* variable counteracted the impacts of *Unit Age* to some extent, but not generally enough to reverse filtering direction. For example, downward filtering rates seem to rapidly increase from years 0 to 50, with the impact to repeat incomes being equal to a 44% decrease in repeat income or an odds ratio of 2.23 that a unit is affordable at the 50% of AMI threshold (i.e., 2.23 times as likely to be affordable as new unit). By year 100,

⁵² This is the square of a unit's age that is divided by 100 so that units aged 0 to 100 would have a Unit Age U value of 0 to 100 (e.g., $100^2 = 10,000$ and $10,000/100 = 100$)

however, impact of age to repeat incomes is an estimated 45% decrease in repeat incomes or an odds ratio of 2.01 that a unit is affordable at 50% of AMI. Thus, age-related impacts to filtering are most prevalent in the first 50 years before plateauing though not reversing entirely. That said, the *Unit Age U* variable was not significant in the renter-end specifications, perhaps indicating that unit age has a more linear relationship with renter-occupied units while owner-occupied units may be the driver of the overall observed “U” relationship in filtering rates.

The final specifications in this chapter evaluated the relationship between unit-level adequacy issues and downward filtering. While retaining the controls from previous specifications, this analysis showed that unit-level inadequacy had a strong (negative) impact on repeat incomes, meaning it was associated with more downward filtering. Furthermore, this relationship held even when including a control for low neighborhood rating, though that variable did have a statistically significant relationship with filtering outcomes. Interestingly, descriptive statistics indicated that inadequacy issues rise with unit age, as expected, which is interesting since older units are also associated with less downward filtering. This could simply be explained by there being very high-quality historic units that are unlikely to downward filter as well as very poor-quality units that are more likely to downward filter due to inadequacy issues, though that is not clear based on the outputs described here.

Another interesting outcome was an interaction term between *MaxRehab* and *Renter (Base Year)* in the repeat income model. This interaction term showed that units initially occupied by renters that have a gut rehab see a strong upward swing in repeat incomes. Given the evidence of downward impact from inadequacy, inadequate rental units that are rehabilitated may be particularly vulnerable to upward filtering. Descriptive statistics show that gut rehabs are happening (or identified by survey respondents) far more frequently in owner-occupied units

compared to rental units, so this relationship may also be in part driven by rehabilitated rental units that then transition to owner-occupancy. That said, when running the same regression on the renter-end subsample, similar impacts from gut rehabs on rental units are observed. These results also seem to align broadly with the third and fourth hypotheses in 4.4, with gut rehabs negatively impacting the affordability of rental units, evidence that inadequacy is more prominent amongst older (and rental) units, and affordable units tending to have more inadequacy issues and higher chances of removal from the housing stock. While these relationships are somewhat specific to housing tenure, these results provide further context for the relationship between unit age and filtering that other scholars have discussed (Palm et al., 2020; Skaburskis, 2006) as well as further illuminating possible challenges in preserving the NOAH stock that is more likely to have maintenance issues and long-term financial stability (Garboden & Newman, 2012).

CHAPTER 5: Spatial variation of filtering: how dynamics change based on geography and housing market characteristics

5.1 Introduction/overview

This analysis will evaluate how filtering varies across geographic regions and housing market characteristics. Outside of simply evaluating outcomes by geography, this analysis will seek to understand how housing market costs, housing production levels, and gentrification impact filtering rates. This analysis will use the same general analytical approach as *Chapter 4* and measures filtering in the same manner. As a result, the next subsection (*4.2 Measures and variables*) is brief and is focused on describing which variables will be used to tabulate the data and briefly reiterating how results will be reported. For more specifics on how filtering measures are calculated, please see *3.3 Filtering Measures*.

This chapter builds upon prior work that has found uneven rates of filtering across geographic regions (Liu et al., 2021; Rosenthal, 2014; Spader, 2024; Weicher et al., 2017). This analysis will build upon this existing body of research in a couple ways. First, it will focus on the most recent AHS data available (post-2015) to better understand the most recent filtering trends and dynamics in the United States⁵³. Second, similar to Spader (2024), this analysis will also compare trends based on housing market conditions, specifically changes in housing production and housing price appreciation⁵⁴. However, this analysis will not simply replicate Spader's (2024) analysis. In addition to using decennial census data to measure changes in housing supply, the analysis will also be repeated using the Wharton Residential Land Use Regulation Index (WRLURI⁵⁵), indices for cost and supply trends, and a supply elasticity measure. While

⁵³ Spader (2024) includes 2015 to 2021 as one of three different panels of AHS data; the others use AHS data from prior to 2015

⁵⁴ As detailed in Chapter 3, I will use the FHFA price index as a measure for home price appreciation

⁵⁵ See <https://real-faculty.wharton.upenn.edu/gyourko/land-use-survey/>

some of these variables are likely correlated, metrics like WRLURI and supply elasticity may better predict a housing market's ability to respond to unmet demand while a pure production measure may not capture that nuance.

As described previously, there have been on-going concerns from housing organizers and low-income, BIPOC communities that increased housing development and gentrification are making housing more unaffordable. Thus, another analysis will be done using the IUF data in order to both identify units located on tracts that are gentrifying and to assess whether neighborhood change has had measurable impacts to filtering rates.

5.2 Measures and variables

This chapter's outcome measures are the same as those outlined in the previous chapter. First, I provide a brief description of how outcomes will be reported, though *4.2 Measures and variables* provides more detail on these calculations. Separately, I describe the variables that will be used to tabulate the data (i.e., the geographies used to cluster data for analysis) in *5.3 Geographical and housing market categorizations*.

As with *Chapter 4* and described in *3.3 Filtering measures*, outcomes for filtering will be reported using two different methods. For each method, the results will be shown in a few different ways in order to better evaluate spatial variation. Of note, since this chapter uses CBSA-level variables in the base model used in *Chapter 4*, with one small change. Since the CBSA-level variables are time invariant, including CBSA fixed effects would cause data

convergence⁵⁶, so the CBSA and Census Division dummy variables are not included for analyses in *Chapter 5* or *Chapter 6*.

For the *repeat income* method:

- A. Overall change in real household income over time (expressed as 5-year log change in real income) for units with at least one turnover.
- B. Percentage of units (with at least one turnover) that had a negative change (i.e., shifted to lower income households) in real income.

For the *gross rent threshold* method:

- A. Number of affordable units lost during the time frame analyzed. This will be calculated by measuring the number of units that were affordable at the 50 percent of AMI threshold and quantifying the number of those that were no longer affordable by the end of the time period analyzed (i.e., filtered upward). This will give me an estimation of the total number of affordable units that filtered upward during this time period.
- B. Number of unaffordable units that became affordable during the time frame analyzed. This will be calculated by measuring the number of units that were unaffordable at the 50 percent of AMI threshold in the base year and quantifying the number of those that became affordable by the end of the time period analyzed (i.e., filtered downward). This will give me an estimation of the total number of unaffordable units that filtered downward during this time period.
- C. An aggregation and comparison of (a) and (b) to understand the number of overall additions and losses to the affordable housing stock during this time period.

⁵⁶ The CBSA-level variables reflect cost and supply trends during the study period but do not vary by survey year. Thus, all units within a given CBSA have a single value for a given housing market variable (e.g., CBSA change in total units).

5.3 Geographical and housing market categorizations

This analysis will cluster geographies in several ways. Since the 15 largest metropolitan areas are included and identified in the integrated national sample, results will be, in part, delineated by these geographies. Similarly, Census Divisions delineate broader regions (e.g., Pacific, Mid Atlantic, etc.) by which outcomes can be tabulated. For the regression analyses, CBSA-level market characteristics (tract-level in the case of the gentrification analysis) related to both housing supply (e.g., housing production, regulatory environment) and housing costs (e.g., changes in median rent or home prices) will be included to evaluate how different market conditions impact affordability. Below is a description of the specific variables that are used to evaluate filtering variation. These descriptions are important to contextualize *5.4 Policy questions to be addressed*, which describes the relevant policy questions and the empirical strategies deployed to answer them.

5.3.1 Variables used to categorize data

Below are detailed descriptions of the variables used to categorize data as well as where the data sources for these variables. In general, data is being categorized in one of three ways: (1) geography, (2) housing cost characteristics, and (3) housing supply characteristics. Below is a detailed description of the variables, organized by those categories.

Geography:

Census Region and Division. The national PUF includes designations for both Census Region (higher level) and Division (lower level) that can be used to analyze geographic differences. Below are the Regions and their associated sub-divisions⁵⁷:

A. Northeast

⁵⁷ See [this map](#) for further detail of which states make up these divisions and regions.

- a. New England
- b. Middle Atlantic

B. Midwest

- a. East North Central
- b. West North Central

C. South

- a. South Atlantic
- b. East South Central
- c. West South Central

D. West

- a. Mountain
- b. Pacific

Housing cost characteristics:

Home price appreciation. Following Spader (2024), I will use the FHFA's home price index to measure how home prices have changed over time. This data can be used to estimate price changes at various geographic levels, including zip code, census tract, county, or metropolitan area. Similarly, Zillow has index for home prices (ZHVI) that will be used as CBSA-level variable.

Rent cost appreciation. Using another Zillow variable (ZORI), changes to relative rent levels within a CBSA will be used as a measure to evaluate how changing rent levels impact filtering outcomes.

Gentrifying tracts. Using IUF data, gentrifying census tracts are identified and their filtering outcomes can be compared against other tracts. Following Ding et al. (2016),

“*gentrifiable*” tracts will be identified as those with median household incomes below the citywide median income in the base year of this analysis (2015). Of those tracts, gentrifying tracts are those with above citywide median percentage increase in either its median gross rent or median home value (rent, in this analysis) and an above citywide median increase in its share of college-educated residents. These variables are available via the ACS at the tract level. “Non-gentrifying” tracts would be those not experiencing one or both of those above median percentage increases (home prices and share of college-educated residents).

Housing supply characteristics:

Changes in housing units. Using decennial census data, I can estimate the general growth of housing units at various geographic levels (e.g., county, metropolitan, tract). ACS data is also used, though the decennial census was ultimately used in all regression analyses.

Wharton Residential Land Use Regulation Index (WRLURI). Using survey data that quantifies the restrictiveness of local land use regulations (Gyourko et al., 2021)⁵⁸, I will include the WRLURI18⁵⁹ index as another housing market-level variable. This index’s interquartile range runs from -0.68 (25th percentile) to 0.62 (75th percentile) and a standard deviation of 1 by design. A higher WRLURI value indicates that a jurisdiction is more highly regulated.

⁵⁸ Data is publicly available here: <https://real-faculty.wharton.upenn.edu/gyourko/land-use-survey/>

⁵⁹ WRLURI18 is the 2018 update of the dataset that was initially created in 2006

5.4 Policy questions to be addressed

Using the variables outlined in 5.3.1 *Variables used to categorize data* above will be used in order to for analyses across metropolitan regions and other geographic units (e.g., census tracts). Below are several policy questions and the corresponding empirical strategies to answer them.

5.4.1 *How do filtering outcomes vary by geography?*

This is the most straightforward analysis, which would begin by simply clustering observations by Census Region and Subdivision as well as displaying results by the 15 metropolitan areas included in the national sample. A focus of this analysis includes comparing coastal and non-coastal regions and comparing filtering outcomes, as prior researchers have found slower filtering rates in these areas during earlier time frames.

5.4.2 *How do housing and production cost trends impact filtering outcomes (e.g., higher- vs. lower-cost appreciation housing markets)?*

Using IUF data, this analysis imputes CBSA-level indicators for rent cost and home price appreciation and evaluate their impacts on filtering rates. This quantifies how outcomes differ depending on the measure used for housing cost appreciation (home price versus rents) and how filtering dynamics vary between high- and low-cost markets.

Further analyses would evaluate how CBSA-level supply characteristics impact filtering rates independently. These impacts will be evaluated independent of housing cost characteristics first before including variables for both supply and demand characteristics are included to understand how filtering is jointly impacted by those characteristics. Therefore, a stronger understanding of how impacts in cities with high-cost, high-supply (i.e., low WRLURI, high-unit increase, or large jurisdiction size) might contrast with those in high-cost, low-supply or low-cost, high-supply, etc.

5.4.3 How does gentrification impact filtering outcomes?

Following the definitions outlined in 5.3.1 *Variables used to categorize data*, this analysis would tabulate filtering results based on whether a tract is *gentrifying*, *not gentrifying*, or *non-gentrifiable* (i.e., census tracts with above median citywide incomes in 2015). This analysis will include controls for housing production and cost appreciation as well as WRLURLI or other variables to evaluate whether gentrification's impact to filtering, controlling for CBSA-level housing market conditions⁶⁰.

Recent research has found low-income residents in gentrifying tracts are no more or less likely to move than low-income residents in other areas (Ding et al., 2016; Dragan et al., 2019), though they may also be more vulnerable to evictions (Ramiller, 2022). However, other researchers have found evidence of Black households being vulnerable to displacement in tracts experiencing extreme gentrification and in surrounding tracts as well (Christafore & Leguizamon, 2019). Lastly, evidence that filtering may be particularly sensitive to neighborhood characteristics makes the investigation of neighborhoods in the midst of change worthwhile (Anenberg & Kung, 2020; Sommerville & Holmes, 2001). Regardless, understanding more about how gentrification impacts these households and filtering dynamics more broadly warrants further examination⁶¹.

⁶⁰ Housing unit production could be evaluated at CBSA, county, PUMA, or tract level. Mast (2023) finds vacancy chains spread well beyond the immediate area of a new development; thus city-level controls are used in the forthcoming analyses.

⁶¹ Liu et al. (2021) find that filtering indeed slows on gentrifying tracts, though their study analyzes owner-occupied units whereas this study is focused on rental units.

5.5 Hypotheses

Below are several hypotheses that will be used to guide these analyses and are informed by prior research on filtering outcomes.

- (1) *Filtering rates will be lower in specific regions (West and Northeast), but variation will be more prominent based on the regulatory environment (WRLURI) and housing supply changes. However, housing market demand characteristics will more prominently dictate filtering rates.* Research consistently finds lower rates of filtering in high-cost, supply constrained markets in the Northeast and West. I expect to affirm this trend, but also believe that home cost appreciation may be the biggest predictor of filtering rates, even more so than production shifts. Evaluating how filtering varies by both supply and cost variables will test this hypothesis and perhaps provide more clarity on which characteristics have been more impactful in recent years.
- (2) *Similarly, gentrifying tracts (and other geographies) have experienced lower filtering rates regardless of the broader housing market trends.* Largely, following the logic discussed in hypothesis (1), demand trends seem capable of overwhelming supply shifts. Specifically, I expect that a gentrifying tract in a high-production market has a lower-than-average filtering rate, regardless of supply trends, particularly driven by amenity effects, proximity to city centers, new housing stock, and natural geographic features that attract high-wage and high-skill workers (Bond & Coulson, 1989; Brueckner & Rosenthal, 2009; Couture & Handbury, 2023; Diamond & Gaubert, 2022; Hwang & Lin, 2016; Lee & Lin, 2018).
- (3) *Gentrifying tracts will experience both more development (increased supply) and cost appreciation, but this will result in the loss of units affordable to very low-income*

households. Gentrifying areas theoretically will attract more investment due to their changing demographics and perhaps lower resistance to new development compared to wealthier areas with higher rates of homeownership. While this increase in development may lower repeat incomes to some degree compared to areas with less development, it may also result in the loss of very low-income units whose rents may increase more drastically in the short-term. It would also follow that higher cost markets with less NOAH might expect more drastic replacement (and displacement) of low-income households on gentrifying tracts (Brummet & Reed, 2019; Couture & Handbury, 2023; Freeman, 2005).

These hypotheses are focused on both understanding broadly how filtering varies by geography and market characteristics. Additionally, these hypotheses will further characterize the nature of filtering by evaluating different supply and demand characteristics simultaneously. The focus of this chapter is understanding spatial variation of filtering based generally on housing market characteristics. The analysis in *Chapter 6* further evaluates variation based on household characteristics to better understand whether the process of filtering is inequitably distributed based on ethno-racial and socioeconomic characteristics.

5.6 Does filtering vary geographically throughout the U.S.? Where is downward filtering more or less frequent?

While prior research has shown lower rates of downward filtering in West and Northeast regions (Liu et al., 2021; Rosenthal, 2014), Spader's (2024) findings for more recent years do not show much evidence of downward filtering at all, though those results are not strictly based on geography. While I still expect point estimates with lower downward filtering for those two regions, I also expect that across regions downward filtering to be slower or even generally upward filtering compared to prior analyses. This would coincide both with Spader's (2024) more general conclusion that downward filtering has broadly slowed in recent years and recent trends in home price growth.

Using the same panel constructed from national AHS data (2015 to 2023) in *Chapter 4*, the mean change in logged repeat income for unsubsidized units as well as the percentage of units with negative changes in income (i.e., downward filtered) will be compared across U.S. regions. Similarly, for the gross rent threshold approach, I will calculate the share of units that shifted above/below the specified rent threshold (50% of AMI). For both methods, filtering is measured at the CBSA-level in order to compare filtering outcomes across cities and regions during the 2015 to 2023 period.

5.6.1 Repeat income outcomes

In this section, data on the 15 largest CBSAs as well as clustered data for non-metros and non-oversampled metros is presented to understand how filtering is varying across the largest cities in the United States. *Table 18* (p. 111) shows descriptive statistics on overall filtering outcomes for these locations. The CBSAs are shown by region, broken out by four general regions within the United States: Northeast (Boston, New York City, Philadelphia, and Washington D.C.), Midwest (Chicago and Detroit), South (Atlanta, Dallas, Houston, and

Miami), and West (Los Angeles, Phoenix, Riverside, San Francisco, and Seattle). Particularly since several past researchers have found that downward filtering is slower on the coasts, the West and Northeast in particular, it is worth understanding how regional variation trends are prevalent during this study period.

Starting with the repeat income changes (i.e., the mean logged change in 5-year repeat income), outputs are shown in the second column. In general, these results seem to align with prior research as the CBSAs with the highest increases in repeat incomes are located in the Northeast (New York City and Philadelphia) and West (Los Angeles, Riverside, and Seattle). While two of the individual CBSAs with the lowest changes in repeat incomes were from the South region (Houston and Washington DC), Boston was the only other CBSA with a negative change in repeat incomes so regional trends are not necessarily indicative of CBSA-level outcomes.

Additionally, this table shows both Midwest cities (Chicago and Detroit) as well as non-metro areas having fairly high growth in repeat incomes during the study period. In fact, the only region netting more downward filtered units than upward filtered units is the South (estimated in the right most column of the table), driven by filtering outcomes in Dallas, Houston, and Washington DC. *Table 1* in *Chapter 4* already showed that nationally units have generally been filtering upward more than downward, this table just identifies the regions where these trends are more or less pronounced geographically.

Table 18: Filtering outcomes by CBSA and Census Division, 2015 to 2023, repeat income measure

	CBSA	Mean Change in Repeat Income	% DF	% UF	DF (units)	UF (units)	Total Units	Net Units DF
<i>Northeast</i>	Boston	-2.9%	52.1%	47.9%	247,961	227,657	475,618	20,305
	New York	49.8%	41.7%	58.3%	734,461	1,025,428	1,759,888	(290,967)
	Philadelphia	37.5%	43.1%	56.9%	210,398	277,947	488,345	(67,549)
<i>Midwest</i>	Chicago	23.5%	49.7%	50.3%	454,804	461,150	915,954	(6,346)
	Detroit	22.6%	45.3%	54.7%	201,341	243,169	444,509	(41,828)
<i>South</i>	Atlanta	15.0%	48.1%	51.9%	314,011	338,924	652,935	(24,912)
	Dallas	6.5%	52.9%	47.1%	519,957	462,502	982,460	57,455
	Houston	-3.6%	52.8%	47.2%	392,166	350,986	743,151	41,180
	Miami	18.0%	48.8%	51.2%	329,747	345,665	675,412	(15,918)
	Washington DC	-6.1%	52.4%	47.5%	392,467	355,631	749,099	36,836
<i>West</i>	Los Angeles	29.1%	48.9%	51.1%	724,523	756,050	1,480,573	(31,526)
	Phoenix	10.1%	49.6%	50.4%	283,055	288,070	571,125	(5,015)
	Riverside	25.7%	48.4%	51.6%	219,500	234,005	453,505	(14,505)
	San Francisco	3.8%	52.2%	47.8%	263,530	241,756	505,286	21,774
	Seattle	30.2%	46.5%	53.5%	237,196	273,068	510,264	(35,872)
	Non-Metro	29.8%	47.2%	52.7%	1,751,626	1,953,214	3,708,196	(201,588)
	Non-Sampled Metro	9.0%	49.5%	50.5%	8,706,078	8,873,388	17,583,066	(167,310)
<i>Census Divisions</i>	Middle Atlantic	39.6%	44.2%	55.8%	1,541,864	1,943,280	3,485,145	(401,416)
	New England	18.5%	47.3%	52.7%	670,501	746,539	1,417,040	(76,038)
	East North Central	23.9%	48.5%	51.5%	2,229,675	2,366,483	4,599,514	(136,808)
	West North Central	18.4%	48.3%	51.5%	1,105,199	1,177,300	2,286,099	(72,102)
	South Atlantic	6.5%	50.6%	49.3%	3,358,240	3,272,367	6,631,608	85,874
	East South Central	7.3%	49.2%	50.8%	860,662	889,352	1,750,014	(28,690)
	West South Central	3.6%	51.5%	48.5%	2,140,963	2,020,089	4,161,051	120,874
	Mountain	10.1%	47.7%	52.3%	1,268,092	1,389,956	2,658,047	(121,864)
	Pacific	15.7%	49.2%	50.8%	2,807,625	2,903,243	5,710,868	(95,618)

As shown in *Chapter 4*, there is significant filtering variation across housing tenure types and shifts, *Table 19* on the next page displays how filtering varies across cities from the integrated national sample by tenure shifts. Of note, this table indicates that neither “owner to renter” nor “renter to renter” units are significantly filtering downward in nearly all of these cities. Contrary to past research that has shown filtering to be slowest in the West and Northeast, changes to repeat incomes are actually lower in the West than the Midwest, though the Northeast does have the least amount of downward filtering.

Table 19: Descriptive statistics on filtering outcomes, by CBSA and tenure shift

	Geography	Owner to Owner		Renter to Owner		Owner to Renter		Renter to Renter	
		Mean Change in Log Income	Weighted N	Mean Change in Log Income	Weighted N	Mean Change in Log Income	Weighted N	Mean Change in Log Income	Weighted N
Northeast	Boston	0.288	189,552	1.984	34,829	-0.662	27,078	-0.534	224,159
	New York	0.803	534,990	1.806	163,547	-0.710	73,287	0.206	988,064
	Philadelphia	<i>0.414</i>	226,530	1.101	32,560	0.305	37,549	0.220	191,705
Midwest	Chicago	0.147	411,030	0.993	69,749	0.762	47,489	0.127	387,686
	Detroit	0.216	221,959	0.470	33,669	-0.121	26,397	0.244	162,485
South	Atlanta	0.047	258,953	0.713	54,556	<i>0.817</i>	45,296	0.034	294,130
	Dallas	-0.118	330,266	-0.138	65,005	0.647	62,117	0.137	525,071
	Houston	0.045	234,219	0.291	42,217	0.715	48,408	-0.201	418,307
	Miami	0.247	214,991	0.984	64,476	0.272	43,253	-0.020	352,692
	Washington DC	-0.028	285,700	0.703	57,224	-0.756	46,612	-0.118	359,563
West	Los Angeles	<i>0.366</i>	389,854	0.596	100,772	-0.211	111,679	<i>0.286</i>	878,268
	Phoenix	0.337	203,678	0.903	64,301	-0.316	36,302	-0.216	266,845
	Riverside	0.063	178,938	1.027	59,071	0.619	26,902	0.148	188,594
	San Francisco	0.081	169,455	0.931	41,507	0.171	44,750	-0.164	249,574
	Seattle	0.595	186,876	0.849	33,328	-0.340	29,585	0.096	260,475
	Non-Metro	0.601	1,668,842	0.543	287,613	0.464	295,667	-0.131	1,456,073
	Non-Sampled Metro	0.299	6,804,909	0.450	1,207,147	0.026	1,081,598	-0.121	8,489,413

	Geography	Renter Involved		Renter End		Total (all shifts)	
		Mean Change in Log Income	Weighted N	Mean Change in Log Income	Weighted N	Mean Change in Log Income	Weighted N
Northeast	Boston	-0.239	286,066	-0.548	251,237	-0.029	475,618
	New York	0.365	1,224,898	0.143	1,061,351	0.498	1,759,888
	Philadelphia	<i>0.342</i>	261,814	0.234	229,254	0.375	488,345
Midwest	Chicago	<i>0.306</i>	504,924	0.196	435,175	0.235	915,954
	Detroit	0.235	222,550	0.193	188,882	<i>0.226</i>	444,509
South	Atlanta	0.218	393,982	0.138	339,426	0.150	652,935
	Dallas	0.158	652,194	0.191	587,188	0.065	982,460
	Houston	-0.073	508,933	-0.106	466,715	-0.036	743,151
	Miami	0.148	460,421	0.012	395,945	0.180	675,412
	Washington DC	-0.081	463,399	-0.191	406,175	-0.061	749,099
West	Los Angeles	<i>0.264</i>	1,090,719	0.230	989,947	0.291	1,480,573
	Phoenix	-0.030	367,447	-0.228	303,146	0.101	571,125
	Riverside	0.383	274,567	0.207	215,496	0.257	453,505
	San Francisco	0.016	335,831	-0.113	294,324	0.038	505,286
	Seattle	0.133	323,388	0.051	290,060	0.302	510,264
	Non-Metro	0.050	2,039,354	-0.030	1,751,740	0.298	3,708,196
	Non-Sampled Metro	-0.042	10,778,157	<i>-0.104</i>	9,571,010	0.090	17,583,066

p<0.10, **p**<0.05, **p**<0.01

5.6.2 Gross rent threshold outcomes

The filtering outcomes by CBSA using the gross rent method provide further context as to how filtering dynamics are varying across the largest cities in the United States. *Table 20* shows the estimated number and percentage of units by filtering type. The cities with the highest rates of units that are *Always Unaffordable* include Dallas, Los Angeles, Miami, New York City, and Riverside. On the other hand, Chicago, Detroit, and Philadelphia have the highest rates of units that are *Always Affordable*. Interestingly, New York City and San Francisco have the highest estimated rates of Downward Filtering, though they also have a large stock of rent-stabilized housing units that are not necessarily accounted for in this data. Regardless, the *%DF* and *%UF* columns indicate that nearly all CBSAs have more units filtering downward than upward from 2015 to 2023 using the 50% of AMI threshold.

Table 20: Filtering outcomes by CBSA, 2015 to 2023, gross rent threshold measure

CBSA	AU	%AU	AA	%AA	DF	%DF	UF	%UF
Atlanta	898,821	50.4%	356,621	20.0%	298,910	16.7%	230,455	12.9%
Boston	778,663	51.2%	314,244	20.6%	223,234	14.7%	206,028	13.5%
Chicago	1,448,242	48.5%	659,681	22.1%	592,268	19.9%	282,969	9.5%
Dallas	1,269,734	56.1%	366,110	16.2%	323,482	14.3%	305,953	13.5%
Detroit	551,863	35.8%	510,360	33.1%	282,505	18.3%	195,349	12.7%
Houston	1,011,630	50.2%	422,064	20.9%	291,278	14.5%	290,635	14.4%
Los Angeles	2,191,024	58.0%	506,536	13.4%	693,087	18.4%	385,620	10.2%
Miami	976,932	55.3%	267,699	15.2%	344,803	19.5%	177,242	10.0%
New York City	3,196,591	54.8%	739,789	12.7%	1,293,091	22.1%	608,648	10.4%
Philadelphia	810,382	42.6%	500,171	26.3%	354,906	18.7%	235,903	12.4%
Phoenix	784,221	53.9%	246,992	17.0%	236,649	16.3%	186,361	12.8%
Riverside	735,035	61.2%	127,970	10.7%	205,317	17.1%	132,463	11.0%
San Francisco	724,737	50.1%	279,621	19.3%	288,295	19.9%	154,891	10.7%
Seattle	673,915	52.8%	245,570	19.2%	206,484	16.2%	149,830	11.7%
Washington DC	955,752	50.7%	349,187	18.5%	355,522	18.8%	226,063	12.0%

The higher relative growth of housing costs compared to incomes⁶² likely explains some of the discrepancy between the two measures. Specifically, HUD rent levels have increased above the median for many of these cities with places like New York City (+6.4% CAGR;

⁶² See <https://www.jchs.harvard.edu/blog/home-price-income-ratio-reaches-record-high-0>

+63.4% total) and Los Angeles (+5.4% CAGR; +51.9% total) having larger increases in HUD rent levels than the median change during this time period (+4.1% CAGR; +37.5% total)⁶³.

Since HUD limits are meant to be applied to rental units, this table also is diluted by units that are owner-occupied. In order to better understand filtering dynamics amongst renter-occupied units, *Table 21* below shows the same filtering outcomes, but only amongst units that ended as renter-occupied.

Table 21: Filtering outcomes by CBSA, 2015 to 2023, gross rent threshold measure, renter-end units

CBSA	AU	%AU	AA	%AA	DF	%DF	UF	%UF
Atlanta	364,315	67.2%	39,997	7.4%	61,218	11.3%	76,988	14.2%
Boston	293,059	61.4%	69,453	14.6%	49,355	10.3%	65,091	13.6%
Chicago	485,006	56.8%	138,942	16.3%	124,492	14.6%	104,721	12.3%
Dallas	631,247	73.1%	56,743	6.6%	54,908	6.4%	121,192	14.0%
Detroit	192,462	54.0%	68,946	19.3%	37,671	10.6%	57,410	16.1%
Houston	483,442	66.8%	68,965	9.5%	50,803	7.0%	120,692	16.7%
Los Angeles	1,335,812	74.3%	91,425	5.1%	214,652	11.9%	155,887	8.7%
Miami	488,060	76.4%	13,637	2.1%	67,470	10.6%	69,530	10.9%
New York City	1,433,665	60.4%	223,466	9.4%	490,606	20.7%	225,273	9.5%
Philadelphia	253,449	51.9%	102,577	21.0%	56,589	11.6%	76,033	15.6%
Phoenix	342,263	75.3%	23,480	5.2%	28,496	6.3%	60,046	13.2%
Riverside	288,677	79.5%	13,251	3.7%	23,751	6.5%	37,336	10.3%
San Francisco	357,646	62.1%	70,791	12.3%	86,870	15.1%	61,022	10.6%
Seattle	299,025	68.9%	47,870	11.0%	35,616	8.2%	51,664	11.9%
Washington DC	361,190	60.6%	75,228	12.6%	78,658	13.2%	81,014	13.6%

The results in *Table 21* paint a different picture of filtering outcomes amongst the 15 largest CBSAs, with the estimated percentage of units that filtered downward being lower across every one of the CBSAs. Upward filtering rates are similar or even higher amongst these units as well. The net outcomes vary, with some cities having more units filtering upward than downward (e.g., Atlanta, Boston, Dallas, Houston, Seattle) and others having more units filtering downward than upward (e.g., Chicago, Los Angeles, New York, San Francisco). Importantly, New York City is a large share of the downward filtering observed here – nearly 0.5 million units out of a total of 1.5 million units that filtered down across these 15 CBSAs.

⁶³ Author compiled data that calculated CAGR in HUD FMRs from 2015 to 2023

While other CBSAs had about 170,000 more units filter upward than downward, New York City had nearly 270,000 more units filter downward than upward. As mentioned previously, the more expansive stock of unsubsidized but regulated housing units combined with much higher-than-average increases to HUD affordable rent levels could be driving the shift of units from above to below the HUD 50% of AMI threshold. Los Angeles and San Francisco also show net increases in affordable housing units via filtering though both also have rent control laws and larger than average increases to HUD affordability levels during this time frame. *Table 22* below shows descriptive statistics on the outcomes of rent-controlled units (“RC”) versus non-rent-controlled units (“non-RC”) in the four cities with substantial amounts of rent-controlled housing units (Los Angeles, New York City, San Francisco, Washington DC).

Table 22: Filtering outcomes, rent-controlled versus non-rent-controlled units, renter-end units

	AU	AA	DF	UF	N	Total Units
<i>Los Angeles (RC)</i>	69.75%	5.72%	16.23%	8.30%	162	157,734
Los Angeles (non-RC)	74.74%	5.02%	11.53%	8.71%	868	1,640,042
<i>New York City (RC)</i>	50.86%	16.73%	22.32%	10.10%	72	258,473
New York City (non-RC)	61.58%	8.52%	20.47%	9.42%	565	2,114,537
<i>San Francisco (RC)</i>	59.70%	19.49%	16.45%	4.36%	181	124,728
San Francisco (non-RC)	62.71%	10.29%	14.69%	12.31%	609	451,601
<i>Washington DC (RC)</i>	55.15%	23.99%	11.31%	9.55%	21	18,180
Washington DC (non-RC)	60.76%	12.26%	13.25%	13.72%	643	577,910

As expected, rent-controlled units are more likely to remain Always Affordable compared to non-rent-controlled units. The inverse is also true—units that are rent-controlled are less likely to be Always Unaffordable compared to rent-controlled units. With a couple exceptions, rent-controlled units are generally more likely to Downward Filter and less likely to Upward Filter compared to non-rent-controlled units. In total, these four CBSAs have roughly 560,000 units that are subject to some form of rent control within the sample. The substantial number of rent-restricted units in combination with the aforementioned increases to HUD rent levels in these CBSAs is likely skewing outcomes, as opposed to more renter-friendly conditions

in these markets. Of note, the total number of rent-controlled units and share of renter-occupied units appear to be quite low⁶⁴. This could indicate that either these units are underrepresented amongst the sample or, perhaps more likely, some respondents are unaware that their unit is covered by local rent-control policies, which may bias these results by making non-rent-controlled units appear to have more favorable outcomes.

Table 23 on the next page further affirms this is likely the case. This table shows the total number of affordable rental units at the beginning and end of the study period by CBSA as well as the net change in total NOAH units at the 50% of AMI threshold. New York City (+283,553 units), Los Angeles (+76,268 units), and San Francisco (+37,398 units) are the primary CBSAs with more affordable units at the end versus the beginning of the study period. Comparatively, CBSAs with lower increases to HUD levels (though all above the national median) and without substantial numbers of rent-controlled units like Dallas, Detroit, Houston, Philadelphia, and Phoenix have nearly zero or negative growth in affordable rental units during the study period.

The overall estimated increase in NOAH stock during the study period amongst these 15 cities is just under 300,000 total units. However, that is closer to 10,000 when excluding New York City and is a loss of 100,000 total units when excluding San Francisco and Los Angeles as well. While it is difficult to ascertain from these descriptive data, this may indicate that the more regulated housing stock in these cities are resulting in rent increases that are less than increases to HUD income limits and FMRs⁶⁵.

⁶⁴ Government/researchers estimate that rent-controlled units total about 2 million across these same cities. Their individual totals are as follows: New York City (~1 million), San Francisco (~250k), Los Angeles (~667k), and Washington DC (~20,000).

⁶⁵ In particular cities that are subject to HUD's "High Housing Cost Adjustment" end up with rent thresholds that are influenced by high market rents more so than large income shifts. This policy is meant to aid low-income households by upping the income threshold at which households can qualify for subsidized housing.

Table 23: Total affordable rental units 2015 to 2023, gross rent threshold

<i>CBSA</i>	<i>Affordable Rental Units (2015)</i>	<i>Affordable Rental Units (end)</i>	<i>Net Change</i>
Atlanta	103,967	101,215	(2,753)
Boston	127,733	118,808	(8,925)
Chicago	247,365	263,434	16,069
Dallas	157,384	111,652	(45,732)
Detroit	109,339	106,617	(2,721)
Houston	165,824	119,768	(46,056)
Los Angeles	229,808	306,077	76,268
Miami	63,882	81,107	17,225
New York City	430,519	714,072	283,553
Philadelphia	158,872	159,166	294
Phoenix	78,811	51,976	(26,835)
Riverside	43,178	37,002	(6,175)
San Francisco	120,263	157,661	37,398
Seattle	99,292	83,486	(15,806)
Washington DC	134,306	153,886	19,580

5.6.3 Conclusions

When utilizing the repeat income measure, units are generally filtering upward amongst the largest 15 CBSAs that are published within the AHS national dataset. With the exception of units that ended up as renter-occupied in the Boston CBSA, there was not statistically significant downward filtering in any CBSA, regardless of type of tenure or tenure shift. In fact, the majority of units in Detroit, New York City, Philadelphia, and Seattle are filtering upward while no CBSA has a majority of housing units that are filtering downward. Even when narrowing the analysis to units that transition from one renter to another, point estimates were not generally negative nor were they statistically significantly different from zero.

The gross rent threshold measure's results for these 15 CBSAs were much different than the outcomes derived from the repeat income measure. In fact, amongst all units and tenure types

it appears that there are far more units downward filtering than upward filtering. Specifically, this measure indicates that while 3.5 million units filtered upward during the study period, 5.6 million units filtered downward. The resulting net increase of 2.1 million NOAH units would represent a 22.8% increase in NOAH units amongst this sample of housing units nationally. When restricting the sample to units that ended as renter-occupied, this increase fell to just under 100,000 units or a 3.4% increase amongst those units that ended as renter-occupied. An estimated 2.6 million units were both renter-occupied and affordable in the final year, which represented a 300,000 unit (or +13.0%) increase from the base year

However, this measure may be sensitive to unequal shifts in HUD income limits that dictate the 50% of AMI threshold. In particular, high-cost cities that are subject to HUD's "High Housing Cost Adjustment" may have biased results. In fact, cities that were both subjected to large upward shifts in HUD income levels and historically have larger numbers of rent-regulated units (e.g., Los Angeles, New York City, and San Francisco) were the primary source of downward filtering when using this specific measure. These cities also have large rent stabilized housing stocks that likely kept and/or pushed existing units into the affordable tier during this time frame. If these cities are excluded, the net change in affordable rental units would equal a loss of just over 100,000 units, a decrease of roughly 9% in the affordable rental stock. In the following sections when regression models are utilized, the impact of both rent control, CBSA-level fixed effects, tenure shifts, and other variables impacting filtering will be controlled to better understand filtering dynamics in general.

5.7 How do housing cost trends impact filtering outcomes? Which cost measure(s) seem to relate most closely to filtering outcomes?

Prior research has shown lower rates of downward filtering in higher-cost housing markets, both based on broad regional differences (Liu et al., 2021; Rosenthal, 2014; Weicher et al., 2017) and specific housing market characteristics (Spader, 2024). The two major components that impact filtering dynamics seem to be cost-related drivers (e.g., housing price appreciation, gross rent appreciation, and gentrification) and supply-related drivers (e.g., changes in housing supply, jurisdictional size, and regulatory restrictiveness).

This analysis aims to better understand both which variables are the strongest predictors of filtering outcomes and whether supply or demand variables have a stronger impact on these outcomes. My hypothesis is that while both supply- and cost-related variables impact filtering dynamics, cost-related variables will have a greater impact on filtering outcomes. Instead of clustering data by market typologies (Spader, 2024), I will use a model with multiple specifications that include variations of cost and supply variables. To start, I will (a) expand upon the model from *Chapter 4* with housing market supply variable(s) included. The next specification (b) will include only variables related to housing market costs before a final specification (c) that includes both supply and cost variables.

5.7.1 Descriptive data

Before including the various housing market variables into the models, it is worth looking at some descriptive data. This is particularly important since many of these variables are closely related. For example, the WRLURI measures how restrictive land use regulations are and how limiting they are to housing production. This obviously relates to supply as it would likely inhibit housing production, but it also has clear implications for costs—more specific and numerous regulations (e.g., parking requirements and lot size requirements) are likely to increase the costs

to build housing. As is described later in this chapter, the cost measure that is ultimately utilized in the model is the Zillow Observed Renter Index (ZORI)--this is due to its stronger predictive power for the data used in these analyses and the fact that the primary focus of these analyses is the affordability of rental units.

As such, *Figure 2* on the next page shows four different scatter plots of variables compared to the change in ZORI (from 2015 to 2023) amongst the 100 largest CBSAs⁶⁶. For the most part, the ZORI changes do not seem to have a close relationship with any of the other variables outside of the FHFA index changes. This makes sense as they are both housing cost indices, but the ZORI index does not seem to have a clear linear relationship with the supply measures. That said, these high-level relationships do not necessarily tell the entire story as the impacts of these market-level variables still have important implications on individual housing units and affordability. Similarly, ZORI and FHFA indices are useful to understand market-level trends but may obfuscate the within-unit changes that the repeat income and gross rent threshold measures ultimately quantify. The relationship between ZORI and FHFA changes also confirms that home price increases and rental increases are closely correlated, another justification for looking at shifts across tenure types.

⁶⁶ Of the 100 largest CBSAs, 80 had complete data for every scatter plot included here

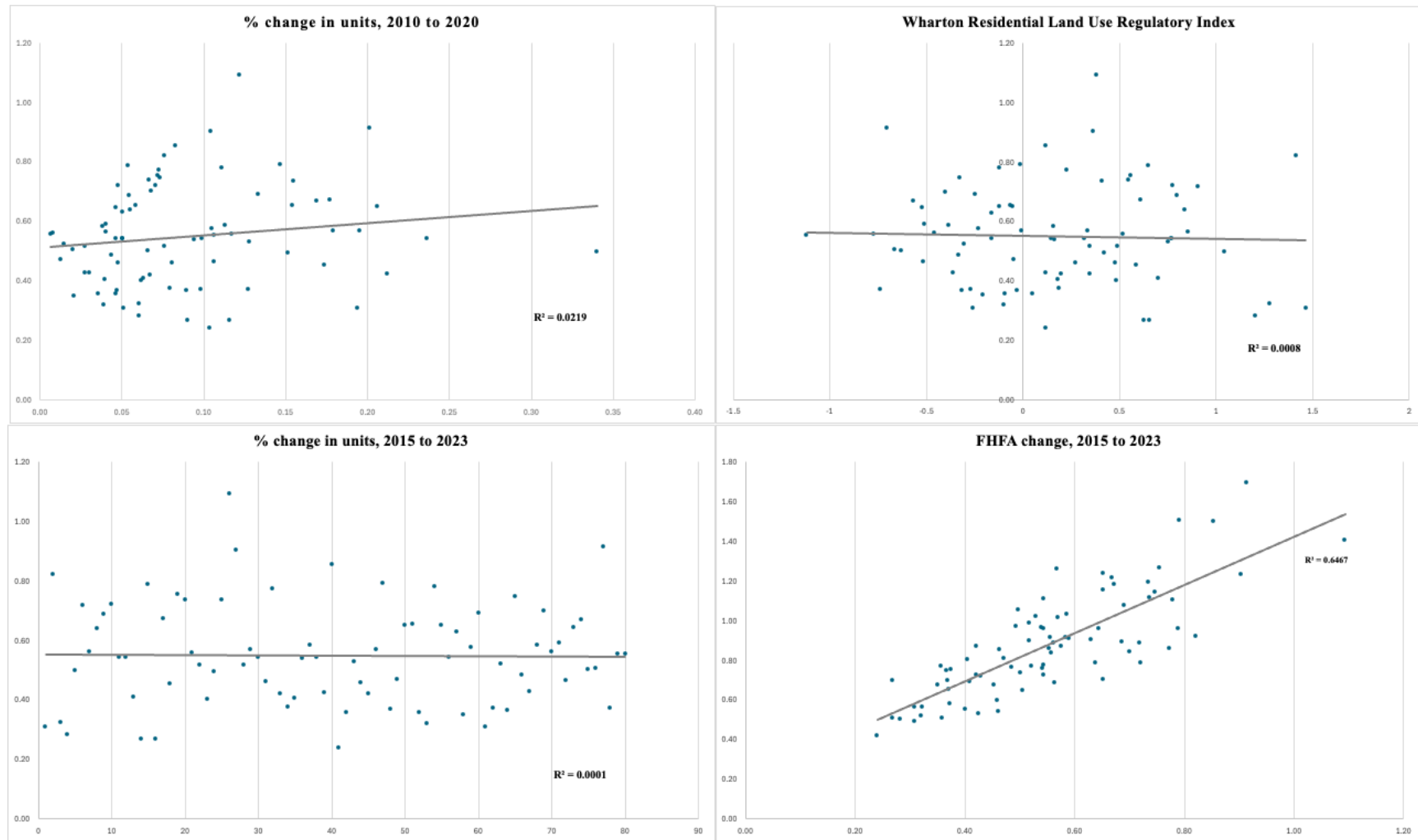


Figure 2: ZORI change vs 2010 to 2020 units change (top left), WRLURI (top right), 2015 to 2023 units change (bottom left), and FHFA change (bottom right)

5.7.2 Regression analyses: repeat income

Several housing market indicators have been imputed to the constructed panel of AHS longitudinal data in order to see which indicators are most impactful to housing affordability changes over time. The base model will be based on the specifications from 4.7, with the housing market variables tested in the model to see which one is the strongest predictor for changes in repeat income.

Housing supply variables

Building upon the model specification in *Section 4.7.1*, the following outputs assess how housing supply trends might impact filtering outcomes. This is meant to better understand which indicator is most impactful to filtering outcomes. As such, the initial specification will use the same variables as used in *section 4.7.1* with the individual addition of each of the below variables.

Elasticity of supply: a variable that estimates the elasticity of supply at the CBSA-level based on WRLURI, housing permits, and other data points derived from recent research (Aastveit et al., 2023).

Housing supply (decennial census): percent change in housing units from 2010 and 2020 decennial census.

Housing supply (ACS 5-year survey): percent change in housing units from the 2015 and 2023 ACS 5-year surveys.

WRLURI (Wharton Residential Land Use Regulatory Index): an index indicating how restrictive local land use regulations are and therefore how difficult it is to increase supply.

Below is the formula used for this model specification:

$$Y = \beta_0 + \beta_1 S_{i,cbsa} + \beta_2 H_{i,t} + \beta_3 H_{i,t+n} + \beta_4 U_{i,t} + y_{i,t} + \varepsilon, \text{ where:}$$

Y = logged change in 5-year repeat income;

$S_{i,cbsa}$ represents housing supply trends at the CBSA-level $cbsa$ for a given housing unit i , including percentage change in housing units⁶⁷ and WRLURI;

$H_{i,Y}$ represents a vector of household variables for the occupant of a given unit i in the base year t ;

$H_{i,t+n}$ represents a vector of household variables for the occupant of a given unit i in the year $t+n$, where n represents the number of years between the base year, t , and final year with necessary data;

$U_{i,t}$ represents a vector of unit-level variables, including *Unit Age*, *Unit Age U*, and *Inadequacy* a given unit, i , during the study period;

$y_{i,t}$ represents time fixed effects, specifically the final year t of data for a given unit i ; and,

ε represents the error term

Table 24 below shows the outputs for each supply variable from the four different specifications.

Table 24: Supply variables regression outputs, repeat income

<i>Measure</i>	<i>Estimate</i>	<i>Standard Error</i>	<i>p</i>
WRLURI	0.2770	0.0761	0.00038
% Unit Change, 2015-2023	-0.0254	0.0061	0.00005
% Unit Change, 2010-2020	-0.0263	0.0059	0.00002
Supply elasticity (2019)	-0.1942	0.1092	0.07752

This table shows that three of the CBSA-level supply variables are significant at the $p < 0.001$ level and that the two different housing unit change variables have very similar point estimates. The supply elasticity variable is only significant at the $p < 0.10$ level. Since the decennial census measure is likely more accurate than the same variable from the ACS (which uses sampling), that measure will be used to measure the supply trends for the CBSAs in this study. However, it is worth noting that *WRLURI* does not necessarily indicate supply changes, rather measuring restrictiveness of local land use, which has been found to correlate with housing prices (i.e., it is more expensive to build, and those costs are passed along to renters

⁶⁷ This will include comparing both the unit trends between 2010 and 2020 decennial censuses and the changes from the 2015 and 2023 5-year ACS

and/or homebuyers). Therefore, this variable was included in a model along with the unit change measure, which resulted in the output shown in *Table 25* below.

Table 25: Regression specification with both WRLURI and Unit Change variable, repeat income

<i>Measure</i>	<i>Estimate</i>	<i>Standard Error</i>	<i>p</i>
% Unit Change, 2010-2020	-0.0183	0.0060	0.00287
WRLURI	0.2206	0.0793	0.00613

This table shows similar point estimates, though lower in magnitude, for each of the two supply variables. As expected, the slightly lower magnitude in the estimates is due to the fact that they do relate to each other to some extent, though the Variance Inflation Factor (VIF) for both variables indicates that collinearity is not an issue⁶⁸. While they are no longer significant at the $p < 0.001$ level, they both remain significant at the $p < 0.01$ level. This output indicates that a 1% increase in total housing units results in a roughly 1.8% decrease in repeat income. On the other hand, every standard deviation of the *WRLURI* measure, which is normalized to have a standard deviation of one, is associated with 22% change in repeat income. Stated differently, in order to negate the impacts of a *WRLURI* that is one standard deviation higher than the median score, there would need to be a 12% increase to housing supply over 10 years.

Importantly, each of these supply variables were statistically significant and their direction correlates with prior findings regarding the relationship between housing supply and filtering. The percentage change in housing units, for example, has a negative coefficient that indicates that a one percent increase in housing units at the CBSA-level is associated with a nearly two percent decrease in repeat income. Similarly, a one standard deviation increase in the *WRLURI*⁶⁹ is associated with a nearly 25% increase in repeat income. Therefore, both the

⁶⁸ While not always mentioned explicitly, VIF was calculated for all regressions to ensure there are no collinearity issues

⁶⁹ The *WRULRI* is normalized so that it has a standard deviation of 1

regulatory environment and actual housing supply trends seem to be meaningful predictors of changes in repeat income amongst unsubsidized units that turned over between 2015 to 2023.

Housing demand variables

Building upon the model specification in *Section 4.7.1*, the following outputs assess how housing cost trends might impact filtering outcomes. This is meant to better understand which housing market demand indicator is most impactful to filtering outcomes. As such, the initial specification will use the same variables as used in *section 4.7.1* with the individual addition of each of the below variables.

Home price appreciation (FHFA): Following Spader (2024), I will use the FHFA's home price index to measure how home prices have changed over time. Specifically, this index will be applied at CBSA-level. For the large CBSAs that are subdivided into Metropolitan Divisions⁷⁰ (i.e., those with > 2.5 million residents), an overall number was still generated by weighted the Divisions by population share.

Home price appreciation (ZHVI): Zillow's Home Value Index (ZHVI) will be utilized as an additional measure of how home prices have changed over time at the CBSA-level. This measure looks at how home value and market changes evolve over time for homes in the 35th to 65th percentile range.

Rental cost appreciation (ZORI): Zillow's Observed Rent Index (ZORI) will be utilized in order to measure specifically how rents are increasing over time at the CBSA-level. This measures changes in repeat index and weights observations in order to ensure

⁷⁰ See <https://www.fhfa.gov/data/hpi/summary-tables?tab=city-hpi>

representativeness of the entire rental stock. This also utilizes rents in the 35th to 65th percentile range and weights those observations to reflect the general rental stock.

The change in these indices will all be calculated by dividing the 2023 value by the 2015 value and subtracting 1 to delineate the overall percentage change from 2015 to 2023. For example, if a CBSA has an index value of 200 in 2015 and 250 in 2023, then the growth would be shown as 0.25 $((250/200) - 1)$. Since low-cost housing markets may show much higher growth despite having generally lower housing prices (i.e., have a low denominator in their 2015 value), the 2015 value for these variables are also included as a control for where the given CBSA started at the beginning of the study period.

Below is the formula used for this model specification:

$$Y = \beta_0 + \beta_1 C_{i,cbsa} + \beta_2 H_{i,t} + \beta_3 H_{i,t+n} + \beta_4 U_{i,t} + y_{i,t} + \epsilon, \text{ where:}$$

Y = logged change in 5-year repeat income;

$C_{i,cbsa}$ represents housing cost trends at the CBSA-level $cbsa$ for a given housing unit i , specifically the percentage change in the aforementioned cost indices as well as the base year index (2015);

$H_{i,t}$ represents a vector of household variables for the occupant of a given unit i in the base year t ;

$H_{i,t+n}$ represents a vector of household variables for the occupant of a given unit i in the year $t+n$, where n represents the number of years between the base year, t , and final year with necessary data;

$U_{i,t}$ represents a vector of unit-level variables, including *Unit Age*, *Unit Age U*, and *Inadequacy* a given unit, i , during the study period;

$y_{i,t}$ represents time fixed effects, specifically the final year t of data for a given unit i ;
and,

ϵ represents the error term

In addition to running three specifications using the three different indices, another specification was utilized for the *ZORI* index. Since the primary focus of this study is on renters, a final specification on units that ended as renter-occupied was also included using the rental-unit

focused *ZORI* index. Table 26 below shows the outputs from including these housing cost variables in the base model.

Table 26: Regression outputs from specifications with housing cost indices, repeat income

<i>Measure</i>	<i>Estimate</i>	<i>Standard Error</i>	<i>p</i>
FHFA % Chg	-0.1848	0.1322	0.16414
FHFA base	-0.0009	0.0007	0.15803
ZHVI % Chg	-0.1597	0.1385	0.25095
ZHVI base	0.0000	0.0000	0.01412
ZORI % Chg	0.3326	0.1879	0.07888
ZORI base	0.0004	0.0001	0.00081
ZORI % Chg (renter end)	0.5112	0.2696	0.05999
ZORI base (renter end)	0.0004	0.0001	0.00309

In the first three specifications, the change variables are not significant at the $p < 0.05$ level, though the base index for both the *ZHVI* and *ZORI* variables are significant at the $p < 0.05$ level. The index that seems to be the most predictive in general is the *ZORI* variable and its p-value is lower for both the base and change variables in the renter end specification. Also of note, the *FHFA* and *ZHVI* variables had negative coefficients, which seems counterintuitive—it implies that units in markets with more home cost appreciation experience lower growth in repeat incomes compared to units in markets with less home cost appreciation⁷¹.

Amongst the control variables, there were also some interesting outcomes of note. While the specifications that included all observations (i.e., all specifications except the *ZORI* renter end) showed a significant impact on repeat incomes from the *MaxRehab* variable and the low neighborhood rating variable, while not significant at even the $p < 0.10$ level had a p-value of ~ 0.20 for the non-renter end model specifications. However, neither of these variables seem to have a meaningful impact on repeat incomes for units that ended as renter-occupied—*MaxRehab*

⁷¹ This sample only includes the 15 largest CBSAs from the integrated national sample—outputs in 5.8 include observations from CBSAs nationally

had a p-value of 0.842 and *NabeRating_low* had a p-value of 0.999 in this specification. This could indicate that filtering dynamics amongst renter-occupied units are less sensitive to neighborhood characteristics and gut rehabs than they are amongst owner-occupied units.

Based on the results from including these cost variables in the base model specification, this study will use the *ZORI* index, particularly as it is focused on rental units in particular. Instead of including multiple specifications using different cost indices, instead this study will include a separate specification that is restricted to units that are renter-occupied when relevant.

Integrated supply and demand variables

After evaluating the best cost and demand predictors for changes to repeat incomes, the *ZORI* index (demand) along with the *WRLURI* index and Decennial Census change in housing units (supply) were identified as the strongest predictors of changes to repeat incomes. To pull this all together, a final specification was run including all three of these variables. This specification is shown below.

$$Y = \beta_0 + \beta_1 C_{i,cbsa} + \beta_2 S_{i,cbsa} + \beta_3 H_{i,t} + \beta_4 H_{i,t+n} + \beta_5 U_{i,t} + y_{i,t}$$

The supply and demand variable outputs from this model are shown below in *Table 27* on the next page. These results indicate that the CBSA-level demand variables (*ZORI* base and growth) do not meaningfully impact repeat incomes when controlling for supply changes and land use restrictiveness.

However, when the *ZORI* variables are removed from the model, the p-value for the *WRULRI* lowers substantially and the magnitude of its coefficient increases slightly. This seems to indicate that land use restrictiveness and *ZORI* may be related though primarily driven by *WRULRI*. Thus, the previous output shown in *Table 26* which only includes the CBSA-level

supply variables, seems to be the strongest predictive model and would indicate that housing supply changes and the relative restrictiveness of local land use regulations are stronger predictors of repeat incomes than rent and home price appreciation metrics.

Table 27: Regression specification including both demand and supply indices, repeat income

<i>Measure</i>	<i>Estimate</i>	<i>Standard Error</i>	<i>p</i>
ZORI % Chg	-0.0068	0.2117	0.97425
ZORI base	0.0000	0.0002	0.89392
Units % Chg, 2010-2020	-0.0182	0.0062	0.00388
WRLURI	0.2061	0.1106	0.06468

5.7.3 Regression analyses: gross rent threshold

This section replicates the outputs from *section 5.7.1*, only this iteration will use the *Gross Rent Threshold* measure for identifying whether a unit is affordable or not. Similarly, this will start with outputs from the base model plus various specifications testing housing supply variables, then separately test housing cost variables, and then finally a specification that integrates cost and supply variables.

Housing supply variables

Building upon the model specification in *Section 4.7.2*, the following outputs assess how housing supply trends might impact filtering outcomes. This is meant to better understand which indicator is most impactful to filtering outcomes. As such, the initial specification will use the same supply variables (i.e., *WRLURI*, supply elasticity, and Census measures for changes to housing supply) from *section 5.7.1* and add them individually to the base model used in *Chapter 4*.

Below is the formula used for this model specification:

$$Y = \beta_0 + \beta_1 S_{i,cbsa} + \beta_2 H_{i,t} + \beta_3 H_{i,t+n} + \beta_4 U_{i,t} + y_{i,t} + \varepsilon, \text{ where:}$$

$Y = \text{AffordableUnit_last}$, a binomial outcome variable that indicates whether a unit is affordable in its last year of the study at the 50% of AMI level (1) or not (0);

$S_{i,cbsa}$ represents housing supply trends at the CBSA-level $cbsa$ for a given housing unit i , including percentage change in housing units⁷² and WRLURI;

$H_{i,t}$ represents a vector of household variables for the occupant of a given unit i in the base year t ;

$H_{i,t+n}$ represents a vector of household variables for the occupant of a given unit i in the year $t+n$, where n represents the number of years between the base year, t , and final year with necessary data;

$U_{i,t}$ represents a vector of unit-level variables, including *Unit Age*, *Unit Age U*, and *Inadequacy* a given unit, i , during the study period;

$y_{i,t}$ represents time fixed effects, specifically the final year t of data for a given unit i ; and,

ε represents the error term

Table 28: Regression supply variable outputs from each specification, gross rent threshold

<i>Measure</i>	<i>Estimate</i>	<i>Standard Error</i>	<i>p</i>
WRLURI	-0.0099	0.0071	0.16632
% Unit Change, 2015-2023	-0.3526	0.0544	0.00000
% Unit Change, 2010-2020	-0.3356	0.0530	0.00000
Supply elasticity (2019)	0.0111	0.0081	0.17433

Table 28 above shows the output of each supply variable tested in each of the three specifications. The estimation and significance level is nearly identical for both estimates of unit change (ACS and Decennial Census data) while the *WRLURI* variable is not significant at the $p < 0.10$ level. Perhaps the most interesting aspect of this is the negative relationship between changes in housing supply at the CBSA-level and likelihood an existing unit will stay or become affordable at the 50% of AMI level. On the other hand, while not significant at the $p < 0.10$ level, the *WRULRI* variable has negative direction which would indicate that units in CBSAs with

⁷² This will include comparing both the unit trends between 2010 and 2020 decennial censuses and the changes from the 2015 and 2023 5-year ACS

more restrictive land use regulations are less likely to be affordable at the end of the study period.

Similar to *WRLURI*, the supply elasticity coefficient is not significant at the $p < 0.10$ level but does have a positive point estimate, indicating that units are more likely to be affordable if they are in markets with more responsive housing supply. As done with the repeat income measure, it is worth evaluating the impacts of both unit change and land use restrictions simultaneously to see if that is more informative than evaluating them independently. *Table 29* shows the outputs of a specification including each of the unit change variables with the *WRLURI* variable included. This is not done with the supply elasticity variable since *WRLURI* is a component of its calculation.

Table 29: Regression specifications with both supply change and WRLURI variables, gross rent threshold

<i>Measure</i>	<i>Estimate</i>	<i>Standard Error</i>	<i>p</i>
WRLURI	-0.0189	0.0075	0.01263
% Unit Change, 2010-2020	-0.3916	0.0565	0.00000
WRLURI	-0.0198	0.0075	0.00900
% Unit Change, 2015-2023	-0.4158	0.0574	0.00000

When the *WRLURI* variable is included along with the unit change variables, both variables are significant at the $p < 0.05$ level. Both variables are negatively correlated with the likelihood that a unit will be affordable at the end of the study period. This means that more units in localities with more restrictive land use regulations are less likely to end up as affordable units and units in markets with more housing unit growth are also less likely to end as affordable.

Housing demand variables

Building upon the model specification in *Section 4.7.1*, the following outputs assess how housing cost trends might impact filtering outcomes. This is meant to better understand which indicator is most impactful to filtering outcomes. As such, the initial specification will use the same variables as used in *section 4.7.1* with the individual addition of each of the same variables used when measuring changes in repeat income: Home price appreciation (*FHFA* and *ZHVI*) and rental cost appreciation (*ZORI*).

After running a separate regression for each measure using the same controls from the base model, the outputs in *Table 30* were generated for the various housing cost variables using the gross rent threshold measure. The two Zillow indices (*ZORI* and *ZHVI*) have the strongest predictive power of these variables, though all of the change variables are significant at the $p < 0.01$ level. Perhaps the most interesting outcome is the renter-end specification using the *ZORI* variables, which shows that units that the likelihood of renter-occupied units being affordable at the end of the study period are more impacted by shifts in housing costs than the base cost level. Essentially, the likelihood of a unit being affordable at the end of the period is more impacted by recent shifts in housing costs than whether or not it is in a high-cost housing market or not.

Table 30: Regression specifications with housing cost variables, gross rent threshold

<i>Measure</i>	<i>Estimate</i>	<i>Standard Error</i>	<i>p</i>
FHFA % Chg	-0.0374	0.0126	0.00362
FHFA base	-0.0201	0.0057	0.00062
ZHVI % Chg	-0.0865	0.0128	0.00000
ZHVI base	-0.0446	0.0095	0.00001
ZORI % Chg	-0.0922	0.0175	0.00000
ZORI base	-0.0343	0.0093	0.00030
ZORI % Chg (<i>renter end</i>)	-0.1780	0.0259	0.00000
ZORI base (<i>renter end</i>)	0.0204	0.0142	0.15463

There is also a key difference between controls between the ZORI and ZORI (renter end) specifications. Specifically, the inadequacy variable is twice the magnitude in the renter end specification while the low neighborhood rating variable had very similar estimates in both models. This would indicate that in terms of their impact on affordability, neighborhood effects are more important to owner-occupied units while inadequacy is more important for renter-occupied units. The unit age variables are also insignificant in the renter-end specification, which could indicate that when controlling for housing market cost trends (and baseline prices), unit age is less important to downward filtering amongst rental units than unit-quality issues.

Regression outputs: integrated supply and demand variables

After evaluating the best cost and demand predictors for the likelihood a unit ends as affordable at the 50% of AMI threshold, the ZORI index (demand) along with the *WRLURI* index and ACS change in housing units (supply) were identified as the strongest predictors of changes to repeat incomes. Since the two-unit supply variables had very similar predictive strengths, the Decennial Census variable was used for consistency with the repeat income model

and the fact that it uses census data rather than a survey sample. As a result, the final specification was run including all three of these variables and is shown below.

$$Y = \beta_0 + \beta_1 C_{i,cbsa} + \beta_2 S_{i,cbsa} + \beta_3 H_{i,t} + \beta_4 H_{i,t+n} + \beta_5 U_{i,t} + y_{i,t}$$

After running this specification, there appeared to be collinearity issues between *ZORI* and *WRLURI*. This was confirmed with a strong correlation between those two variables (0.721) amongst the large metro areas in the integrated national sample. However, *ZORI* and change in *ZORI* are stronger predictors of whether a unit ends as affordable at the 50% of AMI level. While regulatory conditions may be driving both increased development and housing costs, the rent index is the better predictor of outcomes amongst these existing units. This is likely driven by the fact that while stringent regulatory measures do indeed drive up costs, strong demand is also necessary to drive up housing costs. Essentially highly regulated housing markets may or may not have demand that is slowing filtering while high-cost housing markets are likely to be both highly regulated and have slower filtering rates.

Table 31: Regression specifications with supply and cost variables, gross rent threshold

<i>Measure</i>	<i>Estimate</i>	<i>Standard Error</i>	<i>p</i>
% Unit Change, 2010-2020	-0.4788	0.0570	0.00000
ZORI base	-0.0545	0.0099	0.00000
ZORI % Chg	-0.1200	0.0181	0.00000
% Unit Change, 2010-2020 (<i>renter end</i>)	-0.5616	0.0814	0.00000
ZORI % Chg (<i>renter end</i>)	-0.2087	0.0253	0.00000

Additionally, a renter-end specification was run to see how rental units are impacted by these variables and there are some differences. For one, the base *ZORI* level is less predictive for these units (similar to previous results) while the coefficients for both supply and cost shifts are of greater magnitude in this specification. However, it is worth noting a given CBSA may not

have a unit change and *ZORI* change with the same direction, so these shifts may offset each other to some extent. Thus, while units in markets with larger increases in overall units might have slower filtering rates, this impact may be abated to some extent by slower upward cost shifts.

5.7.4 Conclusions

After evaluating the impacts of both housing market cost and supply variables, the results had some variation between both the two measures and the general versus renter-end specifications of these models. Using the repeat income variable, all the supply variables were significant independently and the unit change and *WRLURI* measures were significant even when simultaneously included in a specification. However, the cost variables were not as strong of predictors for repeat income, with the *ZORI* variable being the strongest predictor and even stronger when used in the renter-end specification. After running a specification with both types of variables included, the cost variable was no longer statistically significant, which seemingly indicates that repeat income is more sensitive to changes in supply dynamics than changes to costs.

Using the gross rent threshold, however, *WRLURI* was not a strong predictor when included without any other supply or cost variables. However, when a unit change variable was included along with *WRLURI*, both were strong predictors without any collinearity issues. The cost variables were generally strong predictors of whether a unit ended as affordable using this measure, though the base *ZORI* index was not as strong of a predictor using the renter-end specification, perhaps indicating that renter-occupied units are more sensitive to shifts in cost changes than they are in cost levels across CBSAs. When cost and supply variables were both included in the model, the *WRLURI* variable has collinearity issues with *ZORI*. When just

including *ZORI* and unit change variables, they are all strong predictors and interestingly are all negative in direction, indicating that larger increases in rent costs and larger increases in unit supply are associated with decreased probability of a unit being affordable at the end of the study period. The renter-end specification had similar results only with the coefficients having stronger magnitudes and the base cost index not being a strong predictor (and therefore omitted).

5.8 How does gentrification impact filtering outcomes?

Prior research has shown various outcomes and relationships derived from gentrification. There are some economic benefits to residents (Dastrup & Ellen, 2016), some have found minimal impacts to out-migration (i.e., displacement) though longer distances for moves of low-income households (Dragan et al., 2019) while others have found increases in out-migration for less educated renters (Brummet & Reed, 2019). There is also evidence of differing characteristics for in-movers to gentrifying tracts (Freeman, 2005) and spatial sorting of high-income/highly educated households to areas with newer housing stock (Brueckner & Rosenthal, 2009).

Spatial concentration of high-income households can substantially impact inequality (Fogli & Guerrieri, 2019) and spatial skill sorting has been increasing since 1980 (Diamond & Gaubert, 2022). Some cities have experienced more pronounced growth because of natural features that have an anchoring effect (Lee & Lin, 2018). There has also been some evidence of a relationship between upzoning and the displacement of nonwhite residents in the short-term (Davis, 2021) while racial composition and housing market attributes have been found to impact filtering rates in some cases (Kim & Lee, 2024). As a result, I expect to find that gentrifying

tracts will have lower rates of downward filtering, driven by shifts in neighborhood composition, even in cases where there is an increase in housing supply.

Following Ding et al. (2016), I will categorize census tracts as follows. First, *gentrifiable* tracts are those with median household incomes below the citywide median income in 2015 while all remaining tracts would be considered *non-gentrifiable*. Within this category, a tract would be considered *gentrifying* if it had an increase in share of college-educated residents and median gross rent from 2015 to 2023 that was higher than the citywide increase for either of those measures. The remaining tracts within this category would be considered *not gentrifying*.

This section will start by exploring some descriptive statistics related to *gentrifying*, *not gentrifying*, and *non-gentrifiable* tracts. After evaluating outcomes via these descriptive data, dummy variables for those gentrification categories will be included in an expanded specification of the model used in the prior section (5.7). Thus, the relationship between gentrification and filtering will be evaluated while controlling for various characteristics already determined to impact filtering outcomes (unit age, housing market trends, etc.). Ultimately, this is meant to quantify how tract-level trends are impacting filtering outcomes independently of broader market and unit-specific characteristics.

5.8.1 Descriptive data

As described previously, all tracts in the dataset were organized into three different categories, tracts that are (1) *gentrifying*, (2) are *not gentrifying*, and (3) are *non-gentrifiable*. A tract is *non-gentrifiable* if its median income in 2015 is equal to or greater than the citywide median income while gentrifying tracts are those with increases in college-educated residents and median gross rents that were higher than citywide increases during the study period. To

better understand how these types of tracts vary in basic characteristics, there are some summary statistics in the *Tables 32 and 33* on the next page.

There are a few things evident from these descriptive data. First, *Table 32* shows that gentrifying tracts are seeing drastic changes in the influx of residents with college degrees. These tracts experienced a median increase of 31.5% share of residents with a bachelor's degree between 2010 to 2015 compared to a 2.0% increase on tracts that were *not gentrifying* and a 4.5% increase on tracts that were *non-gentrifiable*. While it is unsurprising that these tracts have higher increases given the classification is based on a higher than CBSA average increase in educational attainment, the chasm is substantial between both the other classifications. While base year rents were quite similar for *gentrifying* and *not gentrifying* tracts, the final year rents were much higher for gentrifying tracts. Overall, about 10% of all tracts are *gentrifying* and about two-thirds of these tracts are located within the 50 largest CBSAs in the U.S.

While *gentrifying* tracts had the largest percentage increase in median rents (20%), *non-gentrifiable* (10%) and *not gentrifying* (7%) tracts also experienced substantial rent increases during this time period. In terms of trends around housing unit supply, the interquartile range for percentage change in housing units shows that *gentrifying* tracts have a similar floor in housing production (i.e., first quartile) as *not gentrifying* tracts while having a similar ceiling as *non-gentrifiable* tracts (i.e., third quartile). This could be interpreted as low-income housing markets generally attracting less new development while markets with more high-income and educated residents being more likely to attract new development—*gentrifying* tracts simultaneously have lower-income residents and larger influxes of residents who are more likely to attract development.

Table 32: Census tract-level characteristics by gentrification category

	<i>Census Tract level</i>					<i># of Census Tracts</i>
	<i>Change in residents with college degree</i>	<i>Median Rent (2010)</i>	<i>Median Rent (2015)</i>	<i>Median Rent Change</i>	<i>Units % Change (IQ Range)</i>	
Gentrifying	31.5	723	885	20.4	(-2, 3.6)	7,616
Not Gentrifying	2	737	781	6.8	(-2, 3.2)	34,253
Non-Gentrifiable	4.5	935	1068	10	(-1.5, 3.6)	32,133

Table 33: CBSA-level characteristics by gentrification category

	<i>CBSA level</i>			
	<i>Change in residents with college degree</i>	<i>Median Rent (2010)</i>	<i>Median Rent (2015)</i>	<i>Median Rent Change</i>
Gentrifying	5.4	846	931	10.4
Not Gentrifying	5.9	842	953	10.4
Non-Gentrifiable	5.8	850	932	10.4

Additionally, *Table 33* shows the median CBSA-level characteristics by tract classifications. Some of the differences are expected given how the tracts are classified—for example, *gentrifying* tracts are more concentrated in cities with lower CBSA-wide increases in educational attainment compared to *not gentrifying* and *non-gentrifiable* tracts. While the median rents are similar in the base and final years for each tract classification, the CBSA-level median rents in 2015 for *not gentrifying* tracts is higher compared to the other two groups. This could indicate that gentrification is more likely to occur in less expensive housing markets or that high-cost markets have stickier housing markets and more concentrated poverty and/or affluence.

Since the analyses will use two different samples from the AHS and they only comprise a portion of all census tracts, *Tables 34* and *35* show descriptive data on the tracts used in these analyses. For the repeat income sample of all units (i.e., renter and owner-occupied), data shows that gentrifying tracts both have lower mean increases in repeat incomes and lower rates of downward filtering (i.e., negative changes in repeat incomes). *Non-gentrifiable* tracts have the largest increases in repeat incomes, which likely makes sense as these tracts may be most likely to attract very high-income households. For tracts that are not gentrifying, it may be that they have more concentrated numbers of very low-income households that are leading to larger upward swings in repeat incomes, though they also are likely not attracting as many higher income households.

However, when narrowing this sample to units that ended as renter-occupied (“renter-end”), data shows that gentrifying tracts have increasing repeat incomes for rental units while rental units on tracts that are not gentrifying have nearly no change in mean repeat incomes and rental units on *non-gentrifiable* tracts had a mean negative change in repeat incomes. Following this, the majority of rental units on *non-gentrifiable* tracts filtered downward while the majority

Table 34: Gentrification descriptive statistics, repeat income⁷³

	All units (repeat income)			Renter-end units (repeat income)		
	% unit growth (2010-2020)	% Change in Repeat Incomes	% Downward Filtered	% unit growth (2010-2020)	% Change in Repeat Incomes	% Downward Filtered
Gentrifying	8.80%	8.68%	48.07%	9.02%	2.13%	48.73%
Not Gentrifying	8.21%	12.56%	49.09%	8.34%	0.44%	50.00%
Non-Gentrifiable	8.38%	16.02%	49.24%	8.37%	-9.92%	52.51%

Table 35: Gentrification descriptive statistics, gross rent threshold⁷⁴

	Renter-end units (gross rent threshold)						
	% Affordable (2015)	% Affordable (last year)	% unit growth (2010-2020)	% Always Affordable	% Always Unaffordable	% Downward Filtered	% Upward Filtered
Gentrifying	33.25%	30.50%	8.54%	18.31%	54.57%	12.19%	14.94%
Not Gentrifying	31.93%	29.32%	7.78%	16.79%	55.54%	12.53%	15.14%
Non-Gentrifiable	23.66%	21.46%	8.00%	11.04%	65.92%	10.42%	12.62%

⁷³ These data were approved for release by the US Census Bureau (CBDRB-FY26-P3221-R13043)

⁷⁴ These data were approved for release by the US Census Bureau (CBDRB-FY26-P3221-R13043)

of units on gentrifying tracts filtered upward. Additionally, the average CBSA-level growth in housing units was higher for gentrifying tracts compared to the other two groups. This is likely expected, as it may merely indicate that hotter housing markets are attracting more development and also have a higher prevalence of gentrifying census tracts.

Table 35 shows the descriptive data on the gross rent threshold sample for renter-end units specifically. Gentrifying tracts actually had the highest prevalence of affordable units in the base year of all types of tracts, though only slightly higher than low-income tracts that were not gentrifying. Each of the tract groups had around a 2.5-point decrease in the share of affordable units from 2015 to the final year of the analysis and again gentrifying units were concentrated more heavily in CBSAs with larger growth of housing units. Gentrifying tracts also have the highest proportion of units that are always affordable though in general the share of each filtering outcome for gentrifying and not gentrifying tracts are closely mirrored while units in *non-gentrifiable* tracts are far more likely to always be unaffordable and less likely to filter upward or downward.

Taken together, these data suggest that gentrifying and not gentrifying tracts share some similar traits—units occupied by lower income households are likely more vulnerable to upward filtering and certainly more so when there is an influx in higher-income households (i.e., gentrifying areas). While somewhat mixed, it does appear that increased supply seems more likely to be directed towards gentrifying or *non-gentrifiable* tracts, meaning areas with concentrated low-income populations may be less likely to attract new housing developments. When focusing on units that end as renter-occupied, the repeat income measure shows that rental units are generally filtering upward on gentrifying tracts and filtering downward on *non-gentrifiable* tracts. The gross rent measure shows that the vast majority of units did not shift

affordability over time, regardless of tract type, and upward filtering was more prominent than downward filtering across all three groups. That said, downward filtering is more prominent on both gentrifying and not gentrifying tracts compared to *non-gentrifiable* tracts, meaning that filtering seems to be more closely aligned with baseline economic characteristics rather than whether or not there is a recent influx of higher-income households.

5.8.2 Regression analyses: repeat income

In addition to the new variables introduced in 5.7, this specification of the model includes two dummy variables that identify whether a unit was on a tract that is *gentrifying* or *not gentrifying*, with *non-gentrifiable* being the reference category. As a reminder, *non-gentrifiable* tracts are those with median household incomes that are not below the citywide median income. Therefore, these two dummy variables are comparing how tracts that started off as below the citywide median income to all other tracts and how those differences vary between tracts that were *gentrifying* and *not gentrifying*.

To start, the outputs of the repeat income models for both all units and renter-end units are shown in *Table 36* on the next page. The specification with all units shows that the impacts of being on *gentrifying* and *not gentrifying* tracts are negative on repeat incomes compared to units located on tracts that are *non-gentrifiable*. That said, units on tracts that are *not gentrifying* have lower repeat incomes compared to those that are on *gentrifying* tracts. In fact, the change in repeat incomes is about 19% higher for units located on *gentrifying* tracts compared to those on tracts that are *not gentrifying*.

Table 36: Gentrification regression outputs for all units and renter-end units, repeat income model⁷⁵

All Units			Renter-end Units		
Variable	Estimate	p-value	Variable	Estimate	p-value
<i>(Intercept)</i>	2.6650	0.0000	<i>(Intercept)</i>	1.8850	0.0000
<i>Gentrifying</i>	-0.3775	0.0004	<i>Gentrifying</i>	-0.1756	0.1781
<i>NotGentrifying</i>	-0.5865	0.0000	<i>NotGentrifying</i>	-0.4129	0.0000
<i>elast19</i>	0.1988	0.0747	<i>elast19</i>	0.2496	0.1314
<i>ZORI_base</i>	0.4771	0.0000	<i>ZORI_base</i>	0.5526	0.0005
<i>ZORI_15_23</i>	0.2764	0.1777	<i>ZORI_15_23</i>	0.4331	0.1373
<i>UnitsChg_10_20</i>	-0.7455	0.2118	<i>UnitsChg_10_20</i>	0.0373	0.9602
<i>UnitAge</i>	-0.0123	0.0106	<i>UnitAge</i>	-0.0127	0.0521
<i>UnitAgeU</i>	0.0084	0.0337	<i>UnitAgeU</i>	0.0081	0.1228
<i>NabeRating_low</i>	-0.1106	0.1835	<i>NabeRating_low</i>	-0.0242	0.8155
<i>Inadequacy_FYOne</i>	-0.3624	0.0165	<i>Inadequacy_FYOne</i>	-0.2704	0.1410
<i>RentControl_BY</i>	-0.2795	0.5270	<i>RentControl_BY</i>	-0.3655	0.4081
<i>HCV_BY</i>	0.8709	0.0017	<i>HCV_BY</i>	0.7749	0.0114
<i>HCV_FY</i>	-1.9020	0.0000	<i>HCV_FY</i>	-1.8050	0.0000
<i>Renter_BY</i>	-0.5921	0.0000	<i>Renter_BY</i>	-0.2715	0.0387
<i>Tenure_shift</i>	0.1260	0.1233			
<i>MaxRehab</i>	0.1626	0.0706	<i>MaxRehab</i>	-0.0319	0.8875

N = 14000

N = 7800

⁷⁵ These data were approved for release by the US Census Bureau (CBDRB-FY26-P3221-R13043)

Interestingly, while the *ZORI base* and *ZORI growth* variables have positive coefficients, indicating they positively impact repeat incomes, and the percentage change in housing units negatively impacts repeat incomes, the elasticity variable had a positive effect on repeat incomes. While this on the surface may seem confounding—a more responsive housing market leading to more upward filtering—this might make sense given the inclusion of the other variables. Technically, the change in housing units controls for the actual shifts in CBSA-level housing supply while the *ZORI* index measures changes in rents, so controlling for those variables, the elasticity is positively correlated with repeat incomes possibly because it correlates with incomes in general. Essentially, this measure may be simply showing that markets with more highly responsive supply are in part reacting to upward swings in local incomes and economic growth.

The renter-end specification offers additional insight to the filtering dynamics for renters in particular. In general, the gentrification impacts are similar to the specification with all units included. However, the magnitude of their negative effects relative to *non-gentrifiable* tracts is far lower. Essentially, while repeat incomes are still lower on these tracts, the magnitude is more muted, though the higher intercept would still indicate that changes in repeat incomes are still lower for renter-end units, even on *gentrifying* and *not gentrifying* tracts. Renter-end units are also more sensitive to percentage change in *ZORI* and *ZORI* base while not being responsive to changes in housing units. While the magnitude of impact from a renter occupant in the base year is of lower absolute magnitude, it is still negative in this specification. This would indicate that repeat incomes are lower in renter-to-renter turnovers compared to owner to renter turnovers, as has been shown in the descriptive statistics in earlier chapters. The impact of gut rehabilitations is also insignificant for renter-end units, while having an upward impact on repeat income for all units.

Overall, while filtering is more prominent on *gentrifying* tracts compared to high-income tracts that are *non-gentrifiable*, it is slower on *gentrifying* tracts compared to similar tracts that are *not gentrifying*. This is true in specifications for both all units and renter-end units and the difference in repeat incomes between *not gentrifying* and *gentrifying* tracts is almost identical, with repeat incomes on *gentrifying* tracts being about 21% lower for all units and 19% lower for renter-end units compared to those on *not gentrifying* tracts. Repeat incomes for renter-end units are more sensitive to baseline housing market costs and growth, though not sensitive to changes in housing units at the CBSA level.

5.8.3 Regression analyses: gross rent threshold

The outputs when analyzing gentrification impacts on the gross rent threshold measure are shown in *Table 37* on the next page. As with the repeat income measure, this table shows two different specifications—one specification that includes all observations/units and another that shows the outputs for renter-end observations/units only. Since this is a binomial logistic regression, the outputs show the log-odds of a unit being affordable at the 50% of AMI threshold in the final year.

To start, the specification with all units shows that units on *gentrifying* and *not gentrifying* tracts are more likely to end as affordable compared to units on *non-gentrifiable* tracts. This is to be expected, as *non-gentrifiable* tracts are those with higher incomes and, as shown in 5.8.4, generally have lower concentrations of affordable housing nationally. What is less expected is the fact that units on *gentrifying* tracts are more likely to filter downward than units on tracts that are *not gentrifying*. Additionally, while the *ZHVI base* and *ZHVI growth* variables both have negative coefficients and the *supply elasticity* variable is positive, the *CBSA-level unit growth* is negative.

Table 37: Gentrification regression outputs for all units and renter-end units, gross rent threshold⁷⁶

All Units			Renter-end Units		
Variable	Estimate	p-value	Variable	Estimate	p-value
<i>(Intercept)</i>	-1.1470	0.0000	<i>(Intercept)</i>	-1.1040	0.0021
<i>Gentrifying</i>	0.2868	0.0000	<i>Gentrifying</i>	0.2791	0.0015
<i>Not Gentrifying</i>	0.2120	0.0000	<i>Not Gentrifying</i>	0.2042	0.0066
<i>ZHVI (base)</i>	-0.1182	0.0000	<i>ZORI (base)</i>	-0.4523	0.0000
<i>ZHVI (growth, 15-23)</i>	-0.2706	0.0001	<i>ZORI (growth, 15-23)</i>	-1.7120	0.0000
<i>Supply elasticity</i>	0.2928	0.0000	<i>Supply elasticity</i>	0.3908	0.0005
<i>CBSA units (growth, 10-20)</i>	-0.9021	0.0018	<i>CBSA units (growth, 10-20)</i>	-3.2730	0.0000
<i>Unit Age</i>	0.0236	0.0000	<i>Unit Age</i>	0.0121	0.0382
<i>Unit Age "U"</i>	-0.0162	0.0000	<i>Unit Age "U"</i>	-0.0036	0.4220
<i>Low Neighborhood Rating (2015)</i>	0.0668	0.1140	<i>Low Neighborhood Rating (2015)</i>	0.0750	0.2639
<i>Inadequate (last year)</i>	0.1068	0.1520	<i>Inadequate (last year)</i>	0.2249	0.0594
<i>Rent Control (2015)</i>	0.4556	0.0108	<i>Rent Control (2015)</i>	0.3955	0.0278
<i>Voucher holder (2015)</i>	-0.5060	0.0002	<i>Voucher holder (2015)</i>	-0.4926	0.0016
<i>Voucher holder (last year)</i>	1.1990	0.0000	<i>Voucher holder (last year)</i>	1.4400	0.0000
<i>Renter (2015)</i>	-0.9176	0.0000	<i>Renter (2015)</i>	0.1479	0.1886
<i>Tenure shift</i>	-0.1216	0.0547			
<i>Gut Rehab</i>	0.1227	0.0026	<i>Gut Rehab</i>	0.1267	0.6240
<i>Affordable (2015)</i>	1.4040	0.0000	<i>Affordable (2015)</i>	1.4660	0.0000
<i>N = 35,500</i>			<i>N = 11,500</i>		

⁷⁶ These data were approved for release by the US Census Bureau (CBDRB-FY26-P3221-R13043)

As outlined in the descriptive data, *gentrifying* tracts on average are in CBSAs with about 1% higher growth in housing units compared to *not gentrifying* tracts. Thus, some of the difference between these outcomes would be eroded by the higher supply growth since the *CBSA-level unit growth* does have a negative coefficient. Additionally, there is some evidence that median rents could be higher amongst the units that are on *not gentrifying* tracts (see *table 35*), which given the static nature of the 50% of AMI threshold could be slightly biasing the outcomes. Lastly, the gap between tract and CBSA-level median rents and tract-level median rents is wider for *not gentrifying* tracts than *gentrifying* tracts, so there may be some catching up to broader market prices happening on tracts that are initially marked as *not gentrifying*.

Shifting to the renter-end specification, the intercept and coefficients for the gentrification dummy variables are nearly identical. However, while the directions are the same, the magnitude of impact for all of the housing market variables are all far greater in this specification—*ZORI base*, *ZORI growth*, *Supply elasticity*, and *CBSA unit growth*. Given the far larger coefficient for the *CBSA unit growth* and the fact that *gentrifying* tracts are more focused in CBSAs with more housing unit growth, systemic differences in where *gentrifying* and *not gentrifying* tracts are located may explain a portion of this gap—a 1% higher increase in CBSA-level unit growth is associated with about a 3% reduction in the likelihood a given renter unit is affordable.

Overall, renter-end units are far less likely to end up as affordable in high-cost markets and those with high price appreciation. These units are also more likely to end or remain affordable when they are initially occupied by renters as well and even more likely if those units were either affordable in the base year and/or are subject to some form of rent control. The somewhat confounding outcome of units on *gentrifying* tracts being more likely to be affordable

at the end of the study period. However, it is worth noting that *gentrifying* tracts had a higher baseline share of affordable units compared to *not gentrifying* tracts. While this was included as a variable in the model, it also may be indicative of systemic differences between these types of geographies. Furthermore, it may be that in the relatively small number of areas experiencing gentrification (~10% of all tracts) have place-based policies to protect renters in those tracts (e.g., right to counsel, more active tenant organizing, and housing services).

5.8.4 Conclusions

There is evidence that units in *gentrifying* neighborhoods are filtering differently compared to units in other neighborhoods. The analyses using the repeat income method revealed that changes to repeat incomes on *gentrifying* tracts were higher than those on tracts that were *not gentrifying* but lower compared to those that were not *gentrifiable*. Thus, it could be said that incoming residents to existing units (and neighborhoods) are more likely to have relatively higher incomes on both *non-gentrifiable* and *gentrifying* tracts compared to low-income tracts that are *not gentrifying*.

On the other hand, the gross rent threshold measure reveals slightly different outcomes. Specifically, units on *gentrifying* tracts are more likely to stay or become affordable at the 50% of AMI threshold than both units on tracts that are *not gentrifying* and *non-gentrifiable*. While higher-income *non-gentrifiable* tracts may be reasonably expected to have slower downward filtering rates, even compared to *gentrifying* tracts, it seems a bit odd that units on *not gentrifying* tracts are less likely to be affordable compared to those on *gentrifying* tracts.

While rent control is included as a variable in these analyses, it is worth noting that there is some evidence that rent control policies may suppress rent levels, even in units not covered by those policies, and that longer-term tenants often receive discounts relative to newer renters

(Pastor et al., 2018). As previously mentioned, *gentrifying* tracts are concentrated in large cities that are more likely to have such policies, not to mention stronger tenant protections. Within such cities, it may be that landlords in neighborhoods with high numbers of rent-controlled units and unmet housing demand may have the most incentive to deregulate such units (Angst et al., 2025). This could, in theory, lead to newly deregulated units and/or more development sites in tracts where rent-controlled units are concentrated that could pave the way for more NOAH in the wake of lost subsidized housing.

In both measures of affordability, the renter-end specifications were more sensitive to both baseline housing market costs and cost trends compared to the all units specifications. However, while repeat incomes for renter-end units were not sensitive to CBSA-level housing unit growth, the gross rent measure was more sensitive to the same unit growth variable in the renter-end specification. This could indicate that there is a negative impact on the affordability of very low-rent units from increased housing development, at least in the short-term, or that markets that attract high amounts of development simply are also losing more deeply affordable housing.

5.9 Discussion

This chapter evaluated how spatially derived differences may relate to filtering variation in the United States. In 5.6, geographic variation of filtering was evaluated. While the repeat income measure generally showed upward filtering (i.e., increasing repeat incomes), the gross rent measure showed substantial downward filtering during the same period. This was likely driven by large upward shifts in the defined 50% of AMI rents due to HUD's "High Housing Cost Adjustment" in cities like New York City, Los Angeles, and San Francisco. These cities

also have large amounts of rent-regulated housing, which may further bias the outcomes as units that are regulated are even more likely to see their rents rise less than the HUD adjusted rents during this specific time frame.

The first policy question outlined in 5.4 was how filtering varied geographically across the U.S. Overall, the trends observed geographically somewhat follow the outcomes reported in prior research and align with the first hypothesis in 5.5. Specifically, the West and Northeast have high growths in repeat incomes, though so does the Midwest region during this time period, while the South sees lower growth in repeat incomes. The trends of repeat incomes generally increasing over time aligns with recent research as well (Spader, 2024). While the gross rents measure's outcomes on the surface show strong trends of downward filtering, this can be explained largely by both recent changes in HUD rents and the characteristics of the housing stock in the cities with the largest increases in HUD rent levels. Additionally, as described briefly in *Chapter 4*, refinancing activity likely lowered both nominal and real housing costs for many owner-occupied units during this time frame due to historically low interest rates during the COVID-19 pandemic (Gerardi et al., 2021). Regardless, further exploration of how these filtering outcomes were shaped was needed, so 5.7 shifted focus to how housing-market level characteristics were impacting outcomes.

5.7 specifically evaluated how various supply and demand related variables related to filtering outcomes. CBSA-level variables were used to understand the impact of both supply and demand related dynamics impact filtering. The results showed that repeat incomes were more sensitive to supply variables and the WRLURI measure for land use restrictiveness compared to cost measures like the FHFA or Zillow indices. For the gross rent threshold measure, there were both supply and cost variables that the outcome variable was sensitive to, even when both were

included in the same specification. While there was not a metric across measures and specifications that was universally the best predictor of a unit's affordability, there is evidence that rental units were more sensitive to changes in CBSA-level housing costs than baseline cost levels. While this intuitively makes sense given that both cost indices and HUD thresholds indicate how expensive a given housing market is in general, baseline costs still had significant impacts on affordability outcomes on the specification that was inclusive of all units. Thus, when controlling for other variables, filtering of very low-income units is slower in high-cost markets even though HUD rents have risen more rapidly in those same markets during the study period. That said, supply seems to have a stronger impact on repeat incomes, meaning affordability of units in general may be more greatly impacted by supply characteristics. Taken together, this could both align with prior research that supply shifts open up units to lower-income households and even lowers nearby rents (Asquith et al., 2020; Mast, 2023; Pennington, 2021) and indicate that increased supply alone is not necessarily effective in creating NOAH units that are affordable to very low-income households. Regardless, the hypothesis that cost trends are more dominant than supply trends was not evident in these outcomes, though the gentrification analyses in 5.8 do provide a bit more context to this nuanced relationship.

The impacts of gentrification were evaluated in 5.8 in order to understand how neighborhood change impacts filtering dynamics. Comparing *non-gentrifiable* (tracts with median household incomes above the citywide median) neighborhoods to those that are *gentrifying* (above citywide average gains in educational attainment and median rents) and *non-gentrifying* (not above citywide average gains in one or both of those same metrics). For both measures, there are distinct differences between the three neighborhood types. In some cases, *gentrifying* tracts are more similar to *non-gentrifying* areas (e.g., units are more likely to end as

affordable and repeat incomes are lower) and in other ways they are more similar to *non-gentrifiable* tracts (e.g., attract more housing development). While the repeat income measure showed that *non-gentrifiable* tracts had the highest repeat incomes followed by *gentrifying* tracts and then *not gentrifying* tracts, the gross rent threshold measure output indicated that units in *gentrifying* tracts were more likely to end as affordable than those in *not gentrifying* areas. This likely warrants further exploration, though given amenity effects and numerous other measurable benefits to low-income households (Brummet & Reed, 2019; Dastrup & Ellen, 2016), it may be that low-income residents are more assertive in exercising their rights or other resources to remain even as tensions escalate and both landlord and tenant behaviors shift in these areas (Angst, Rosen, De Gregorio, et al., 2025; Angst, Rosen, Painter, et al., 2025; Duvisac et al., 2022).

In sum, this chapter has shown that there are numerous spatial characteristics that impact filtering dynamics for housing units in the U.S. Specific regions and cities have distinctly different filtering outcomes from one another with the West, Northeast, and Midwest all experiencing more pronounced upward filtering in comparison to the South. Supply and demand characteristics of housing markets are also important in shaping filtering outcomes at the unit level, with higher housing cost appreciation and more restrictive land use regulations restricting affordability in general while repeat incomes were generally lower in markets with more housing supply growth. On the other hand, increased housing supply was associated with units being less likely to be affordable at the 50% of AMI threshold. Thus, more robust housing development may generally make units affordable while also putting more pressure on units that have very low rents, at least in the short term. There also seem to be distinct outcomes across *gentrifying*,

non-gentrifying, and *non-gentrifiable* areas, though impacts to affordability vary between the two outcome measures.

CHAPTER 6: How householder characteristics relate to filtering outcomes

6.1 Introduction/overview

In this chapter, filtering dynamics will be tabulated by household characteristics to understand the distributional impacts of filtering. In particular, how filtering differs based on ethno-racial and socioeconomic characteristics of households will be evaluated. In addition to understanding how the benefits (and costs) of downward (and upward) filtering are distributed across ethno-racial groups, a similar analysis will be done on how impacts differ by income tier. The focus remains on evaluating filtering's efficacy at generating very low-income (50% of AMI) housing units, in particular for low-income, BIPOC households, so this analysis will compare how filtering outcomes impact those groups compared to other households.

The AHS includes numerous variables related to both unit and household characteristics. These variables make it possible to analyze filtering dynamics in a way to understand more thoroughly how impacts from downward and upward filtering are distributed and to what extent outcomes differ by the ethno-racial and socioeconomic characteristics of households. In sum, this analysis seeks to understand how filtering varies across ethno-racial and socioeconomic groups nationally.

6.2 Measures and variables

As with the previous analyses, the outcome variable we are concerned with is the change in affordability of a given housing unit over time. Filtered units will be identified using two different methods, with the outcomes of these methods being evaluated separately. One method is the repeat income model (Liu et al., 2022; Rosenthal, 2014; Spader, 2024) and the other is a measure of rent relative to AMI thresholds (Weicher et al., 2017). Details and examples of these

methods are available in 3.2 *Research Design*. Like the prior analyses in *Chapters 4* and *5*, filtering outcomes will be defined as one of the following:

- *Downward filtered*: unit that was unaffordable in the base year that becomes affordable over time.
- *Upward filtered*: unit that was affordable in the base year that becomes unaffordable over time.
- *Always affordable*: unit that was affordable in the base year that stays affordable over time.
- *Always unaffordable*: unit that was unaffordable in the base year that stays unaffordable over time.

As with prior analyses, in some cases filtering types are not delineated, but rather only whether units begin or end as affordable. For all methods of measuring filtering, household incomes will be derived from a variable that is readily available in the AHS (“HINCP”). This variable is defined as “the sum of all types of income for all household members aged 16 and over.”⁷⁷ The following subsections provide more detail on how filtering will be measured as well as how results will be presented.

6.3 Household characteristics of interest: ethno-racial, income, etc.

This section describes the various analyses that will be carried out in order to better understand how filtering dynamics vary by household characteristics. Below are detailed descriptions of how data will be tabulated in order to better understand how filtering dynamics

⁷⁷ The full AHS codebook is readily available online: <https://www.census.gov/data-tools/demo/codebook/ahs/ahsdict.html>

vary by various characteristics. The general empirical strategy is outlined, including specific data sources and the variables that will be used.

6.3.1 Analysis of ethno-racial characteristics

To understand how filtering varies by ethno-racial group, this analysis will use the AHS variables of “HHRACE” and “HHSPAN” to identify ethno-racial characteristics of the unit’s primary householder. HHRACE includes response codes for White only, Black only, American Indian/Alaskan Native only, and Asian only, amongst others. Since the Census Bureau’s reports race and ethnicity separately⁷⁸, HHSPAN is also included to identify householders of Hispanic/Latino descent. While there are numerous response codes associated with various identifications of race/ethnicity, this analysis will focus on a few specific groups. Notably, Asian households will be tabulated in this analysis, though with a careful eye towards their margins of error. If outputs seem particularly unreliable, they may be removed, but using the national sample may still provide enough observations to generate some insights.

For both the metropolitan⁷⁹ and national AHS surveys, there is a raking process to ensure different types of households are proportionately represented in the final weights. Amongst the groups prioritized in this raking process are “number of Black persons” and “number of Hispanic persons.” Statistical software packages allow for a calculation of accurate margins of error for subpopulations by incorporating the AHS-provided replicate weights, but other minority populations may have larger margins of error resulting in insignificant results⁸⁰. As a result, this analysis will tabulate results by these HHRACE response codes:

⁷⁸ See <https://www.census.gov/topics/population/race/about.html>

⁷⁹ Documentation for metropolitan and national surveys

⁸⁰ In personal communications with the author, AHS analysts specified Asian/Pacific Islander populations as having such issues of large margins of error, for example.

- 01: White only
 - This group will be cleaned to remove respondents who have a response code of 1: Yes for the HHSPAN variable
- 02: Black only
- 04: Asian only

The analysis will also evaluate filtering outcomes for householders who have the response code 1: Yes for the HHSPAN variable. Notably, this group will have some overlap with householders who have self-identified as 02: Black only or 04: Asian only in the HHRACE variable. However, these groups generally have very little overlap. Amongst the nearly 30,000 observations in the PUF derived gross rent threshold sample, about 1.6% of Asian households and 6.3% of Black households also identify as Hispanic/Latino. In order to keep these groups discrete, Black-Latino and Asian-Latino households will simply be identified as Black and Asian, respectively. Further understanding these groups might be a worth inquiry, but given their small share of the overall population, such investigation is neither the primary interest of the analyses in this chapter nor is there likely enough data to draw meaningful conclusions about these subgroups. In fact, the analyses in this chapter end up primarily utilize a dummy variable for Black or Hispanic households, so the small number of Asian-Hispanic households are the main subgroup interest that is collapsed into a broader racial classification where they are not specifically accounted for.

6.3.2 Analysis of income/affordability characteristics

In addition to tabulating filtering results by ethno-racial characteristics, this analysis will also evaluate how income tiers are impacted by filtering. Specifically, understanding how filtering impacts low-income households. For both measures of filtering (i.e., repeat income and

changes in gross rent), low-income households will be identified as those in the lowest CBSA-level income quartile. Thus, a specific income threshold is not established but rather whether a household has relatively low income compared to other households in the same CBSA. For both measures, the final household occupying a given unit will be the household identified as low-income. The initial occupant's income tier will be controlled for (as has been the case in the other analyses), but low-income households occupying the unit in the final year will be compared to households in other similar units. For the analysis looking at changes in gross rent, the 50% of AMI threshold will be used and the same dummy variable that looks at whether the final occupant is in the first CBSA income quartile or not will be utilized to compare outcomes between low-income and other households.

6.3.3 Analysis of ethno-racial and socioeconomic characteristics

Finally, an analysis evaluating how both ethno-racial and socioeconomic characteristics impact filtering will be done. In this model, both dummy variables (for Black and Hispanic households and low-income households) will be used in order to understand how low-income, BIPOC households are impacted specifically in the filtering process. This analysis simply expands the prior two already described by understand how these characteristics independently and simultaneously impact filtering outcomes. An interaction term (*BlackHisp x LowIncome*), for example, will show how Black/Hispanic, low-income, and low-income, Black/Hispanic households are all differentially experiencing filtering. These dummy variables will also be interacted with housing market variables to discern whether these groups are differentially impacted in certain types of housing markets.

6.4 Hypotheses

Below are several hypotheses related to these analyses, some of which are in direct response to recent research on the same or similar topics.

- (1) *BIPOC households are both most positively and negatively impacted by filtering.* As mentioned previously, housing outcome disparities persist amongst BIPOC households in particular. While I expect a high percentage of households benefiting from downward filtering to be BIPOC households, this will at least in part be driven by their greater need for affordable housing (i.e., income disparities across ethno-racial groups). However, I believe that BIPOC households are also more likely to live in units that eventually filter upward and/or face challenges in attaining housing units that are affordable to them given these existing disparities.
- (2) *BIPOC in particular have more difficulty in attaining good quality, affordable rental units compared to other households.* In addition to persistently differential outcomes across ethno-racial groups for renters (e.g., eviction rates, rent burden, etc.), there is also evidence that Black and Hispanic/Latino homeowners pay a premium for similar housing units as compared to other households (Bayer et al., 2017). Thus, it may be that the various mechanisms causing these other housing-related disparities also impact access to NOAH units for these households.
- (3) *Downward filtered units are still largely unaffordable to low-income and BIPOC households.* There are two reasons for this hypothesis. First, I believe filtering to be a process that can take a long time to come to fruition. While this analysis quantifies when a unit becomes affordable at a certain rent level, it does not identify when an actual low-income household occupies that unit. This sorting process may take additional time.

Second, this sector of the housing market has relatively low supply compared to households in need. While I use the 50% of AMI threshold, the households competing for these units may include not just households earning around 50% of AMI; households earning a good deal less may be even more desperate for housing options and willing to pay rents well above 30% of their income, particularly BIPOC households who have very high rates of being severely rent-burdened (Wedeen, 2021).

6.5 Policy questions to be addressed

As previously mentioned, this analysis seeks to understand how filtering varies across ethno-racial groups and household income levels nationally. This question is deeply relevant to housing policy as disparities across ethno-racial groups persist across a variety of housing outcomes (e.g., eviction rates, homeownership rates, rent burden level) (Bayer et al., 2017; Harrison et al., 2021; Hightower & Fraser, 2020; Preston & Reina, 2021). If policymakers are going to rely on filtering to generate a substantial share of the affordable housing stock, understanding how it impacts existing inequities is of deep importance.

For example, researchers have found that Black and Hispanic home purchasers pay a premium compared to non-Hispanic White purchasers (Bayer et al., 2017) and that, in some cases, Black homeowners in gentrifying areas may not benefit financially due at least in part to racially driven motivations and predatory real estate practices (Hightower & Fraser, 2020). Furthermore, Spader (2024) and other researchers have shown that filtering dynamics are heterogenous and sensitive to various market-, neighborhood-, and regional-level factors. Understanding household-level heterogeneity in filtering outcomes is also important particularly if achieving equitable outcomes is of importance to policymakers. The distributional impacts of

this strategy could also be compared to those derived from tenant- and unit-based subsidies to understand how (and to what degree) the impacts differ.

Lastly, a question that seems to be unanswered by recent research is whether or not downward filtered units are actually affordable to households they have filtered down to. By analyzing rent burden levels of downward filtered units and comparing them to other types of units will provide clarity as to how downward filtered units impact affordability at the household level.

6.6 Do filtering outcomes vary across ethno-racial groups? Do low-income households benefit more or less from filtering compared to other households?

While there has been evidence that market-rate development has induced the filtering process by opening up lower-quality/cost housing units (Mast, 2023) there have also been concerns—and some evidence—that racial composition of neighborhoods can be altered by market-rate development and real estate speculation (Davis, 2021; Kim & Lee, 2025; Louie et al., 2025). There also has been evidence that that Black and Hispanic households might pay a premium for housing compared to non-Hispanic White home purchasers (Bayer et al., 2017) and several other housing outcomes that have documented differences between ethno-racial groups, like evictions (Harrison et al., 2021; Preston & Reina, 2021), participation in housing subsidy programs (Fenelon, 2022; Zapatka & de Castro Galvao, 2023), and impacts from gentrification (Christafore & Leguizamon, 2019). As a result, I expect that Black and Hispanic households will benefit less from filtering (e.g., experience less downward filtering) than other households when controlling for other variables.

Additionally, there is also concern that new market-rate development can lead to short-term price shocks to surrounding housing units (Damiano & Frenier, 2020) and that, even with

filtering effects, market-rate housing may not be effective at providing adequate, affordable housing to very low-income households (Bond and Coulson, 1989; Galster, 1996; Palm et al, 2020; Skaburskis, 2006; Smith-Heimer, 1990; Turner and Wessel, 2019). As a result, I similarly expect that low-income households (e.g., households within the first income quartile) will benefit less from filtering than other households. Furthermore, it may be that low-income, Black and Hispanic renters face particularly difficult circumstances when trying to secure affordable, stable housing.

To investigate whether such differences persist within the panel of AHS data that I have compiled, I will show descriptive statistics on filtering outcomes by race/ethnicity of the final occupant of the unit nationally (i.e., overall change in repeat income, percent of units with negative change, percent of units downward filtered at 50% of AMI). Additionally, similar descriptive data on filtering outcomes across different income levels will be shown to further elucidate possible differences across income levels as well as some data with cross-tabulations of outcomes based on both income level and race/ethnicity.

Additional quantitative analysis will be done by expanding upon the base model from *Chapters 4 and 5* to include dummy variables for the race/ethnicity of the head of household and income quartile for the final occupant of the unit while accounting for other relevant unit and household characteristics. The first model specification (a) will expand on the base model by including the race/ethnicity of the head of household after the final turnover. The second model specification (b) will attempt to control for systemic differences in income between ethno-racial groups by quantifying within-quartile racial differences by including an interaction term.

6.6.1 Filtering variation between ethno-racial groups

To start, understanding how filtering outcomes vary at the broadest level is worth assessing. For both measures (repeat income and gross rent threshold), there is an initial year and a final year. For the repeat income measure, there is also at least one turnover, meaning the household changes. Thus, the repeat income measure may be more illuminating as to how filtering shifts units towards or away from certain types of households (e.g., by race or socioeconomic status).

In general, amongst rental units in the repeat income panel that turned over from 2015 to 2023, *White, non-Hispanic* occupied units are the most likely to stay occupied by households of the same race/ethnicity, with nearly 75% of those units being occupied by *White, non-Hispanic* households in both the initial and final years. For units initially occupied by *Black* and *Latino/Hispanic* households, just under 50% of final-year occupants are of the same race/ethnicity as the initial household while that same number is just over 33% for units occupied by *Asian* households. The share of these various racial shifts amongst rental units are shown in *Table 40*. *Tables 41* and *42* show the mean change in repeat income and percentage of units with negative changes in repeat income by these same shifts in race/ethnicity.

When looking at the mean change in repeat incomes by shifts in the race/ethnicity of occupants, it is clear that this measure is likely sensitive to income disparities along ethno-racial lines. In particular, the mean change in repeat income is negative for units that are occupied by *Black* households regardless of the ethno-racial identity of the initial occupant. Units occupied by *Hispanic/Latino* households also generally have negative shifts in repeat incomes, outside of units that were initially occupied by *Black* households. When looking at the percentage of units

that filtered downward (i.e., had a negative change in repeat income), the majority of renter-end units are filtering downward to all ethno-racial groups except *Asian* households.

Table 38: Base and Final Year Incomes (in 2015\$)

	<u>All units</u>		<u>Renter-end</u>	
	<i>Base Year</i>	<i>Final Year</i>	<i>Base Year</i>	<i>Final Year</i>
All others	\$49,728	\$55,680	\$42,240	\$41,400
Asian	\$71,760	\$78,200	\$67,200	\$60,480
Black	\$38,400	\$40,800	\$34,850	\$34,853
Latino/Hispanic	\$42,000	\$46,750	\$38,000	\$38,990
White, non-Hispanic	\$59,000	\$60,480	\$47,840	\$46,368

Table 39: Percentage of inadequate units, Black and Hispanic/Latino vs All others

<u>Race/Ethnicity</u>	<u>% Inadequate</u>	<u>95% CI</u>
Black and Hispanic/Latino	0.0649	(0.0568, 0.0729)
All others	0.0429	(0.0384, 0.0473)

These descriptive statistics for the repeat income measure are somewhat difficult to untangle—are observed differences due to the relationship between the repeat income measure and income inequities along ethno-racial lines (see *Table 38*) or are there other factors driving differences in filtering outcomes (like unit quality, see *Table 39* above)? Building off the base model used in *Chapters 4* and *5*, the latter portion of this section will include variables for race/ethnicity in order to better understand how outcomes are shaped by ethno-racial characteristics of the householders when controlling for other unit and market variables.

For the gross rent threshold measure, similar descriptive data is presented in tables 40 to 42 (p. 167). In terms of the overall trends in shifts between the race of the head of household, these data mirror the outcomes for the repeat income panel data shown in *Table 38*. In general, this shows the majority or a plurality of transitions are within the same ethno-racial group. Over

40% of units occupied by *Asian* households were also occupied by *Asian* households in the base year while that number is nearly 60% for units occupied by *Black* and *Latino/Hispanic* households and nearly 80% for the *White, non-Hispanic* group.

Table 44 (p. 167) shows the percentage of units that are affordable in the final year based on two categories: shifts in race/ethnicity—units that were occupied by a household with a *different* race/ethnicity in the final year versus the base year versus those that were occupied by households of the *same* race/ethnicity. The point estimates show that units occupied by the same ethno-racial group in the beginning and end of the study period are affordable at a rate over 10% higher than those that experience a change in the race/ethnicity of the household occupying the unit.

Filtering outcomes using this measure also have clear variation—*Black* households are more likely to be in units that are both always affordable and downward filtered than any other ethno-racial group. Upward and downward filtering outcomes make up about 10 to 15 percent of all outcomes across all ethno-racial groups. Given the income disparities amongst renter households outlined in *Table 38*, there does seem to be some mismatch in households of lower incomes (i.e., *Black* and *Hispanic/Latino households*) to those occupying affordable units—*White, non-Hispanic* households have comparable rates of downward filtering to *Hispanic/Latino* households while having a much higher rate of occupying units that are *Always Affordable*.

Ultimately, given disparities in both incomes and filtering outcomes, further investigation is necessary to unwind whether disparities are simply correlated to socioeconomic disparities or if racial disparities exist even independent of systemic differences in incomes. The following subsections use regression analyses in order to better understand these relationships.

Table 40: Racial composition of final occupants, by initial occupant race/ethnicity; renter-end units, repeat income⁸¹

		Race, final occupant				
		All others	Asian	Black	Latino/Hispanic	White, non-Hispanic
Race, initial occupant	All others	8.96%	2.07%	3.34%	2.07%	2.67%
	Asian	5.72%	33.38%	3.91%	4.80%	5.01%
	Black	12.08%	11.05%	48.22%	12.38%	9.32%
	Latino/Hispanic	14.02%	11.96%	14.30%	49.77%	8.66%
	White, non-Hispanic	59.22%	41.54%	30.22%	30.97%	74.35%

Table 41: Average change in repeat income by race/ethnicity shift type; renter-end units, repeat income⁷⁹

		Race, initial occupant					
		All others	Asian	Black	Hispanic/Latino	White, non-Hispanic	Total
Race, final occupant	All others	-0.1954	0.4427	-0.4823	1.2248	-0.2203	-0.0092
	Asian	0.2744	-0.0092	0.3500	0.7475	0.2657	0.2411
	Black	-0.2669	-0.9196	-0.0138	-0.0180	-0.3678	-0.1653
	Hispanic/Latino	0.7951	-0.4302	0.2067	-0.0790	-0.1697	-0.0704
	White, non-Hispanic	-0.7676	-0.0200	-0.0078	0.0780	-0.0011	-0.0163

Table 42: Percent of units with negative repeat income change, by race/ethnicity shift type; renter-end units, repeat income sample⁷⁹

		Race, initial occupant					
		All others	Asian	Black	Latino/Hispanic	White, non-Hispanic	Total
Race, final occupant	All others	48.18%	62.59%	48.38%	34.65%	56.06%	51.80%
	Asian	42.36%	48.73%	40.71%	37.50%	47.69%	45.94%
	Black	62.53%	76.96%	49.06%	50.11%	58.27%	53.54%
	Latino/Hispanic	46.70%	57.29%	47.99%	52.08%	51.56%	51.55%
	White, non-Hispanic	55.38%	57.82%	49.05%	46.16%	50.97%	50.84%

⁸¹ These data were approved for release by the US Census Bureau (CBDRB-FY26-P3221-R13043)

Table 43: Racial composition of final occupants, by initial occupant race/ethnicity; renter-end units, gross rent threshold⁸²

Renter end units		Race/Ethnicity (Final Year)				
Race/Ethnicity (Base Year)	All others	Asian	Black	Latino / Hispanic	White, non-Hispanic	
	All others	23.95%	1.09%	2.64%	0.98%	1.99%
	Asian	4.31%	41.58%	3.78%	3.47%	3.84%
	Black	13.43%	8.02%	59.16%	10.42%	7.75%
	Latino/Hispanic	12.60%	11.50%	11.10%	58.62%	7.44%
	White, non-Hispanic	45.71%	37.80%	23.32%	26.52%	78.98%

Table 44: Percentage of units that are affordable in the final year by race/ethnicity transition type; renter-end units, gross rent threshold⁸⁰

Base vs final year race/ethnicity	% Affordable (last year)
<i>Same race/ethnicity</i>	31.82%
<i>Different race/ethnicity</i>	20.15%

Table 45: Filtering outcomes (percentage) by race/ethnicity of final year household; renter-end units, gross rent threshold⁸⁰

<i>Race/ethnicity</i>	Filtering outcomes, renter-end units			
	<i>Always Affordable</i>	<i>Always Unaffordable</i>	<i>Downward Filtered</i>	<i>Upward Filtered</i>
All others	13.46%	61.46%	10.12%	14.96%
Asian	9.71%	69.95%	10.07%	10.27%
Black	19.47%	51.16%	14.97%	14.40%
Latino/Hispanic	12.76%	60.79%	11.44%	15.01%
White, non-Hispanic	17.01%	57.34%	11.30%	14.36%

⁸² These data were approved for release by the US Census Bureau (CBDRB-FY26-P3221-R13043)

6.6.2 Filtering variation between income groups

Ultimately, given disparities in both incomes and filtering outcomes, further investigation is necessary. In particular, understanding whether disparities are simply due to disparities in incomes or if racial disparities exist even independent of systemic differences in incomes. While the following subsections use regression analyses in order to better understand these relationships, it is first worth looking at what the descriptive data reveals.

Table 46 shows outcomes tabulated outcomes for the gross rent threshold measure by final year income quartile for renter-end units. In general, the outcomes are as expected—higher income households are less likely to live in units that are *Downward Filtered* or *Always Affordable* while being far more likely to be in units that are *Always Unaffordable*. While the percentage of units that *Upward Filtered* is on the face very similar across quartiles, it is actually much higher for the two highest quartiles when considering they had far fewer affordable units in the base year. Considering that context, it can also be said that of the units occupied by the two highest income quartiles of renters in the final year, 55 to 70 percent of units that were initially affordable *Filtered Upward* to those households. For the lower two quartiles, that rate was closer to 35 to 50 percent of units that were initially affordable.

As previously mentioned, the ethno-racial composition of income tiers is not consistent from quartile to quartile. *Table 47* shows the percentage of Black and Hispanic households versus all other households by income quartile for the final year amongst renter-end units. This shows that Black and Hispanic households are more concentrated in the lowest income quartile (40% versus 30%) while having about 6% lower shares of households in the third and fourth quartiles compared to all other households. A more granular tabulation shows that

Table 46: Filtering outcomes by final year income quartile of householder; renter-end units, gross rent⁸³

Income Quartile (FY)	<i>Always Affordable</i>	<i>Always Unaffordable</i>	<i>Downward Filtered</i>	<i>Upward Filtered</i>
1	23.58%	46.07%	16.02%	14.32%
2	15.03%	58.17%	11.94%	14.86%
3	10.64%	66.64%	8.56%	14.15%
4	6.10%	75.40%	5.86%	12.63%

Table 47: Ethno-racial composition by final year income of householder; renter-end units, gross rent⁸¹

<i>Income Quartile (FY)</i>	<i>Black and Hispanic/Latino Households</i>	<i>All other households</i>
1	40.23%	30.41%
2	33.11%	31.94%
3	18.89%	24.42%
4	7.78%	13.23%

Table 48: Repeat income changes by final year income decile and race/ethnicity, renter-end units

Repeat Income Change by Race/Ethnicity, renter end units		
<i>Income Decile (Final Year)</i>	<i>Black or Hispanic HHs</i>	<i>Others</i>
1	-3.8234	-4.2014
2	-0.9437	-1.1016
3	-0.1648	-0.3776
4	0.2318	0.0251
5	0.4939	0.3854
6	0.8925	0.6661
7	1.2521	1.0109
8	1.6010	1.0684
9	2.4169	1.5727
10	3.3417	2.4711

⁸³ These data were approved for release by the US Census Bureau (CBDRB-FY26-P3221-R13043)

Black (over 40%) and Hispanic/Latino (nearly 35%) renters are more concentrated in the first quartile compared to other ethno-racial groups (25-30%).

Table 48 shows how changes in repeat incomes vary by both income decile and race/ethnicity, using the Black and Hispanic/Latino grouping and specifically evaluating renter-end units. This table shows a couple important things. First, as expected, repeat incomes increase as income decile increases for both Black and Hispanic/Latino and all other households. Second, the point estimates for repeat incomes for these two groups have fairly substantial differences within each income decile. Specifically, point estimates show Black and Hispanic/Latino households having higher repeat incomes within each decile.

Thus, the descriptive data certainly shows that outcomes across income tiers and ethno-racial groups show variation, it is not abundantly clear if those differences are solely driven by differences in household income or if race/ethnicity is also driving variation independently of income. Therefore, the following subsections include both of these characteristics and certain interaction terms to better understand how these differences are experienced relative to one another. *Section 6.6.3* uses a regression model to quantify impacts of these characteristics by building upon the models used in *Chapters 4* and *5*. *Section 6.6.4* does the same, only using the gross rent threshold measure.

6.6.3 Regression analyses: repeat income

Building upon the model specification in *Chapter 5*, the following outputs assess how ethno-racial characteristics of occupants might impact filtering outcomes. This is meant to better understand whether ethno-racial characteristics of householders are impactful to filtering outcomes. As such, the initial specification will use the same variables as used in *section 5.8.2* with the individual addition of each of the following variables:

BlackHisp_{i,t+n} is a dummy variable identifying if a given unit *i* is occupied by Black or Hispanic/Latino household in the final year *t+n*;

LowIncome_{i,t+n} is a dummy variable identifying if a given unit *i* is occupied by household with an income that is within the CBSA-level 1st income quartile in the final year *t+n*;

BlackHisp_{i,t+n} x LowIncome_{i,t+n} is an interaction term identifying if a unit *i* is occupied by a household that is both Black or Hispanic/Latino and Low Income in the final year *t+n*;

BlackHisp_{i,t+n} x UnitsChange_{CBSA} is an interaction term identifying the incremental impact of housing supply change (Units Change at the CBSA-level) on units occupied by Black or Hispanic/Latino households in the final year *t+n*;

Instead of isolating each ethno-racial group into their own variables, the race variable used is a binary variable delineating whether the head of household is *Black* or *Hispanic/Latino* (1) or not (0) in the final year. This is also informed by both the descriptive statistics outlined in the prior subsections as well as existing literature which has found evidence that these groups are most likely to have differentiated housing outcomes compared to other ethno-racial groups. This is partially affirmed by testing individual race/ethnicity variables in other specifications, where those variables are generally insignificant at the $p < 0.05$ level.

The results of the first repeat income specification, which includes all units, is shown on the left side of *Table 49* (p. 174). Not all controls are shown in this table, but those excluded either are insignificant or have little change in their coefficients compared to previous outputs. The variables of interest are in bold and reveal several important trends. First, the individual *BlackHisp* variable is not significant at any meaningful level, so it seems that filtering outcomes amongst those households that are not low-income (i.e., have household incomes in the 2nd quartile or higher) do not vary significantly from other types of households. As expected, *Low Income* households have far lower repeat incomes—for this specification this mostly acts as a control alongside the interaction terms.

This leads to the most interesting outcomes from this specification—the two interaction terms. The first, *BlackHisp x Low Income* has a positive coefficient that indicates that units occupied by low-income, Black and Hispanic/Latino households have repeat incomes that are about 16% higher⁸⁴ than other low-income households. This coefficient is significant at the $p < 0.10$ level. The other interaction term of interest is *BlackHisp x Units Change (10 to 20)*, which provides an estimate of how CBSA-level shifts in housing unit growth incrementally impacts Black and Hispanic/Latino-occupied housing units. While the *Units Change (10 to 20)* variable is insignificant at any meaningful level, this interaction term is just outside of the $p < 0.10$ significance level (p-value of 0.1193). The coefficient for this interaction term is -1.413, which indicates that a 10% increase in CBSA-level housing units would be associated with repeat incomes that are roughly 13% lower for Black and Hispanic/Latino households specifically⁸⁵.

Given the direction and magnitude of the *BlackHisp x Low Income* coefficient, there would need to be about 10.6% growth in housing supply at the CBSA-level to offset the higher repeat incomes for low-income, Black and Hispanic/Latino households. Nationally, the median CBSA-level growth rate in housing units was 2.5% from 2010 to 2020, though it is 7.1% for the 100 largest CBSAs. Therefore, these households are still experiencing slower downward filtering, on average, in the majority of housing markets. In fact, only 17 of the 50 largest CBSAs have growth rates above 10% from 2010 to 2020.

⁸⁴ The outcome variable is logged 5-year growth in incomes. Therefore, an un-logged result would equal $\exp(0.2334 - 0.0834) = 1.1618$, indicating these units have income growth about 16.2% higher than other similar units.

⁸⁵ I.e., $0.10 \times -1.413 = -0.1413$; $\exp(-0.1413) = 0.8682$, or 13.2% decrease

Table 49: Outputs from repeat income model specifications with “Black or Hispanic” race variable included, all (left) and renter-end (right) units⁸⁶

Repeat income output, all units				Repeat income output, renter-end units			
Variable		Estimate	p-value	Variable		Estimate	p-value
(Intercept)		3.5630	0.0000	(Intercept)		3.0710	0.0000
Black Hisp		-0.0834	0.4267	Black Hisp		-0.1405	0.2777
Low Income		-3.6140	0.0000	Low Income		-3.3450	0.0000
Black Hisp x Low Income		0.2334	0.0959	Black Hisp x Low Income		0.3077	0.0506
Black Hisp x Units Change (10-20)		-1.4130	0.1193	Black Hisp x Units Change (10-20)		-1.4800	0.2059
Units Change (10-20)		0.0311	0.9588	Units Change (10-20)		0.6762	0.3792
Gentrifying		-0.1585	0.0707	Gentrifying		0.0188	0.8633
Not Gentrifying		-0.2513	0.0000	Not Gentrifying		-0.1131	0.1422
ZORI base		0.3346	0.0004	ZORI base		0.2872	0.0140
ZORI growth (15 to 23)		0.2124	0.2057				
Supply Elasticity		0.1857	0.0449	Supply Elasticity		0.2674	0.0491
<i>N</i> = 14,000				<i>N</i> = 7,800			

⁸⁶ These data were approved for release by the US Census Bureau (CBDRB-FY26-P3221-R13043)

The table on the right-hand side of *Table 49* shows a different specification of this model that only uses observations that end as renter-occupied (“renter-end”). The only other variables excluded in this specification are *ZORI growth* and *Tenure shift*—the former due to lack of statistical significance and the latter since the *Renter (base year)* variable implicitly addresses tenure shifts given all observations end as renter-occupied.

This specification has some important differences, starting with a negative coefficient of greater magnitude for the *BlackHisp* variable, though it is still not significant at the $p < 0.10$ level. The interaction term, *BlackHisp x Low Income*, also is of greater (positive) magnitude in this specification and has a p-value of 0.051. This would imply that low-income, Black and Hispanic/Latino households have repeat incomes about 18% higher than other low-income households. The interaction term *BlackHisp x Units Change (10 to 20)* has a similar magnitude and same direction as the initial specification, though it has a higher p-value (0.2059 compared to 0.1193 in the initial specification). Similar to the other specification, the supply growth required to offset the impacts from the *BlackHisp x Low Income* interaction term would need to be about 11.3%⁸⁷.

Another interesting outcome from this specification is the changes to the gentrification variables—the coefficient for the *NotGentrifying* variable is of much smaller magnitude (though still negative) and is no longer significant at the $p < 0.10$ level. The *Gentrifying* variable is barely positive but has a p-value of 0.863. This seems to indicate that there may be slightly lower repeat incomes on tracts that are *NotGentrifying* but that *Gentrifying* tracts do not have meaningfully

⁸⁷ From 2010 to 2020 the 3rd quartile of supply growth was 11.3% for the 15 largest CBSAs and 11.7% for the 50 largest CBSAs

lower repeat incomes for renter-occupied units after controlling for race/ethnicity and low-income status of the final occupants.

Essentially, this output could indicate that when controlling for the presence of low-income and Black and Hispanic/Latino households, repeat incomes appear to be just as high on *Gentrifying* tracts as they are on higher-income tracts (i.e., *non-gentrifiable*). This could indicate that these markets are somewhat bifurcated—generally increasing incomes are driving up repeat incomes in a portion of the neighborhood and its housing stock, while another portion of the housing stock is occupied by low-income, Black and Hispanic/Latino households who have remained despite the shifting market dynamics. One may point out that the negative coefficient for *low-income* is driving this shift in coefficients for the gentrification variables, but it is worth noting that the *not gentrifying* variable still has a negative point estimate with a p-value of 0.142, indicating that repeat incomes are lower on those tracts compared to *gentrifying* and *non-gentrifiable* tracts even when controlling for the presence of low-income occupants in the final year.

Given there are also controls for unit adequacy and neighborhood ratings, there is also some indication that this dynamic is constant even when controlling for those neighborhood and unit characteristics. As a result, this appears to indicate that low-income, Black and Hispanic/Latino households have *higher repeat incomes* compared to other households, controlling for market, neighborhood, and unit characteristics. This could be driven by lower incomes for the initial occupants (e.g., possibly poorer quality housing units) of the units low-income, Black and Hispanic households tend to occupy. Differences could also be driven by these households needing higher incomes to attain similar housing units to other low-income

households, or a combination of both factors. Regardless, this evidence may point to barriers to these households accessing NOAH units relative to other low-income households.

Some of the differences could be due to slight differences in median incomes amongst first income quartile households, as lower-income White, non-Hispanic households are less likely to utilize subsidized housing programs compared to Black and Hispanic households (Fenelon, 2022; Zapatka & de Castro Galvao, 2023), therefore first income quartile White, non-Hispanic renters may skew slightly lower in terms of incomes. That said, weighting first quartile incomes based on national population share, first income quartile Black and Hispanic/Latino households have incomes about 2.7% greater than other households within the total repeat income sample and 5.2% higher incomes for the renter-end subsample. Outside the fact that transitions are disproportionately within the same ethno-racial groups, these systemic differences are not of a magnitude that would explain the full differences observed in these outputs.

As described in earlier sections, one of the weaknesses of this measure is its sensitivity to systemic differences in incomes while also not considering whether a given unit is actually affordable in terms of its costs. Thus, the next section evaluates these same questions but using the gross rent measure to understand how NOAH units that are affordable at 50% of AMI filter and whether that process sees similar variation along ethno-racial lines.

6.6.4 Regression analyses: gross rent threshold

If you refer back to *Table 43* (p. 168), it shows that the sample used for the gross rent threshold measure has fairly similar race/ethnicity shifts amongst renter-end units as the repeat income sample (see *Table 40*, p. 167). Specifically, White, non-Hispanic households have the highest rates of same race transitions (nearly 80%) over time amongst renter-end units followed by Black and Hispanic/Latino households, whose transitions are within the same ethno-

racial group about 60% of the time. However, when accounting for the population share of those ethno-racial groups overall, the ratio of units sourced from each group to the overall ethno-racial composition shows a slightly different story.

In particular, Black and Hispanic/Latino households are more reliant than White, non-Hispanic households on units derived from households of the same race/ethnicity, though less reliant on such units than Asian households. Perhaps most importantly, Black and Hispanic/Latino households have a much lower expected share of units formerly occupied by White, non-Hispanic households than would be expected if race/ethnicity was a random characteristic⁸⁸. Compared to overall composition, Black and Hispanic/Latino households derive about half as many units as expected from units initially occupied by White, non-Hispanic households than would be expected given their share of these units.

Building upon the model used in *Chapters 4 and 5* and adding similar variables as used in the repeat income specifications in the last subsection, the following gross rent models assess how ethno-racial characteristics of occupants might correspond to filtering outcomes. In particular, these models aim to understand how filtering varies between low-income, Black and Hispanic/Latino households and other groups. As such, the initial specification will use the same variables as used in *section 5.8.3* with the individual addition of each of the below variables:

RaceShift_i is a dummy variable that identifies whether the race/ethnicity of the head of household of a given unit *i* changes from the base to final year;

LowIncome_{i,t+n} is a dummy variable identifying if a given unit *i* is occupied by household with an income that is within the CBSA-level 1st income quartile in the final year *t+n*;

BlackHispi,t+n x *LowIncome_{i,t+n}* is an interaction term identifying if a unit *i* is occupied by a household that is both Black or Hispanic/Latino and Low Income in the final year *t+n*;

⁸⁸ You can find these ratio estimates in *Table 56* in the Appendix

BlackHispi,t+n x *UnitsChangeCBSA* is an interaction term identifying the incremental impact of housing supply change (Units Change at the CBSA-level) on units occupied by Black or Hispanic/Latino households in the final year $t+n$;

BlackHispi,t+n x *ZORICChangeCBSA* is an interaction term identifying the incremental impact of housing cost change (change in the Zillow rent index at the CBSA-level) on units occupied by Black or Hispanic/Latino households in the final year $t+n$;

As with the repeat income specifications, instead of isolating each ethno-racial group into their own variables, the race variable used is a binary variable delineating whether the head of household is *Black* or *Hispanic/Latino* (1) or not (0) in the final year. This decision is derived from previous scholarship on inequities in housing outcomes, descriptive data, and testing different model specifications that isolated individual ethno-racial groups. Also similar to the repeat income specifications, there is a model on all observations and another with the renter-end subsample of units.

The outputs for the all units and renter-end units specifications of this model are shown in *Table 50* on the next page. Starting with the all units specification on the left, there are several commonalities with this output as the repeat income outputs. Again, as expected, the coefficients for both *Black Hisp* and *Low Income* indicate that those households are far more likely to end up in affordable housing units than other households. However, the interaction terms again reveal how low-income, Black and Hispanic/Latino households are differentially impacted by the filtering process. In particular, if the median CBSA change in *ZORI* and *Units Change* are used⁸⁹, the output would indicate that low-income, Black and Hispanic/Latino households are 23.2% less likely to end up in an affordable housing unit compared to other low-income households; using the 3rd quartile *ZORI change* value indicates they are 42.7% less likely to reside in an affordable unit compared to other low-income households.

⁸⁹ The *Units Change* median was calculated using the subset of 209 CBSAs with full *ZORI* data; that median value is +7.3% unit growth from 2010 to 2020

Other coefficients worth noting include the gentrification variables—these indicate that units on *gentrifying* tracts are actually more likely to end as affordable compared to those on both *not gentrifying* and *non-gentrifiable* tracts. This relationship seems counterintuitive—units in areas with more pronounced changes in rents and educational attainment are *more likely* to end up as affordable compared to those in low-income neighborhoods that are not experiencing similar change. However, as mentioned previously, the *Low Income* variable is controlling for the low-income households in the final year, so the positive and very high magnitude coefficient for *Low Income* likely means that units on *Gentrifying* tracts are not downward filtering more than those on *Not Gentrifying* tracts, rather stronger downward filtering on *Not Gentrifying* tracts is driven in part by the shifting demographics of *Gentrifying* tracts (i.e., the displacement of low-income households from those neighborhoods). Given this is not the focus of this specific analysis, this is not evaluated further and precisely why the difference between these coefficients should not be over emphasized.

Importantly, the supply elasticity has a positive coefficient and is significant at the $p < 0.001$ level. This indicates that units in CBSAs with more responsive supply elasticity are more likely to be affordable in the final year compared to units in less responsive housing markets. While the other housing-market level variables are likely impacted by endogeneity issues—markets with the strongest supply upticks are often those with the strongest unmet demand and highest price inflation—this variable arguably gives a more accurate estimation of how more responsive supply shifts impact the affordability of existing housing units.

Table 50: Outputs from gross rent model specifications with “Black or Hispanic” race variable included; all (left) and renter-end (right) units⁹⁰

Gross rent output, all units			Gross rent output, renter-end units		
Variable	Estimate	p-value	Variable	Estimate	p-value
(Intercept)	-4.9970	0.0000	(Intercept)	-7.1210	0.0002
Black Hisp	0.5181	0.0001	Black Hisp	0.9865	0.0001
Low Income	1.0570	0.0000	Low Income	0.7791	0.0000
Black Hisp x Low Income	-0.3625	0.0000	Black Hisp x Low Income	-0.1728	0.1532
Black Hisp x ZORI Change (15-23)	-0.6654	0.0004	Black Hisp x ZORI Change (15-23)	-1.1740	0.0025
Black Hisp x Units Change (10-20)	-0.5028	0.3935	Black Hisp x Units Change (10-20)	-2.6090	0.0435
<i>Units Change (10-20)</i>	-1.0320	0.0071	<i>Units Change (10-20)</i>	-2.2260	0.0331
<i>ZORI Change (15-23)</i>	-0.3845	0.0067	<i>ZORI Change (15-23)</i>	-1.2770	0.0004
<i>Gentrifying</i>	0.2558	0.0000	<i>Gentrifying</i>	0.2196	0.0126
<i>Not Gentrifying</i>	0.1549	0.0001	<i>Not Gentrifying</i>	0.1328	0.0649
<i>Race shift</i>	-0.6991	0.0000	<i>Race shift</i>	-0.4905	0.0000
<i>ZORI base</i>	-0.4560	0.0000	<i>ZORI base</i>	-0.5327	0.0000
<i>Supply Elasticity</i>	0.2159	0.0000	<i>Supply Elasticity</i>	0.4092	0.0005
<i>N = 34,000</i>			<i>N = 11,500</i>		

⁹⁰ These data were approved for release by the US Census Bureau (CBDRB-FY26-P3221-R13043)

Shifting focus to the outputs on the right-side of the table, which is the “renter-end units” specification, there are some important differences in these outcomes. Again, as with the “all units” specification, the coefficients for both *Black Hisp* and *Low Income* indicate that those households are far more likely to end up in affordable housing units than other households. However, the interaction terms again reveal that low-income, Black and Hispanic/Latino households are differentially impacted by the filtering process, particularly depending on the context of recent housing market trends. Specifically, if the median *ZORI change* and *Units Change* are used, the output would indicate that low-income, Black and Hispanic/Latino renter households are 5.1% less likely to end up in an affordable housing unit compared to other low-income households; using the 3rd quartile *ZORI change* value indicates they are 43.4% less likely to reside in an affordable unit compared to other low-income households.

The other variables also shift slightly in magnitude between the two specifications (*all* versus *renter-end* units), but for the most part the coefficients are fairly similar. The intercept is much lower in the renter-end specification (-7.121 versus -4.997) and the renter-end units appear to be more sensitive to both the baseline *ZORI* and *Supply Elasticity* variables. This indicates that renters struggle to find affordable housing in general compared to other households and this disparity is even more pronounced in expensive housing markets with less responsive housing supply.

Overall, there are some key differences between the two specifications, but importantly there do appear to be statistically different filtering outcomes between Black and Hispanic/Latino households and all other households. Importantly, these specifications also controlled for CBSA-

level increases in HUD rents, which had a lot of variation across CBSAs and was inflating the number of units identified as affordable in units with high HUD rent increases in particular⁹¹.

6.6.5 Affordability of downward filtered units, by ethno-racial classification

One question that has yet to be addressed by the previous analyses is whether the units identified as affordable (i.e., negative repeat incomes or below the 50% of AMI threshold in the final year) are actually affordable to the households occupying those units. Since it is entirely a unit that has been identified as affordable by one of these measures is not necessarily affordable to the occupants of that same unit (i.e., these households still may be rent-burdened).

While it may not be a primary concern whether there is a mismatch between a unit's affordability level and its occupants' income level, it certainly feels worthwhile understanding how these measures of unit affordability relate to how affordable said units are to their occupants. In particular, since repeat incomes identify units as downward filtered based in part on the final occupant's household income, the share the income those same households are paying towards housing is relevant. For example, a unit with a negative change in repeat incomes could be comparing two households who are paying very different proportions of their incomes on rent. If the initial household, household A, had a real income of \$8,000 monthly and paid \$2,000 in housing costs, they would be paying 25% of their income on housing costs and would not be considered cost burdened. If the final household, household B, has a real income of \$6,000 monthly and also pays the equivalent (inflation-adjusted) of \$2,000 in housing costs, they would be paying 33% of their income on housing costs and would be considered cost-burdened. That would be identified as having filtered down despite the fact that the occupant household had to pay a much larger proportion of their income to occupy the same unit.

⁹¹ See 5.6.2 in *Chapter 5* for a more detailed discussion of this

To better understand how these measures relate to the actual level of affordability to the households occupying these units, some descriptive data were pulled. Specifically, *Table 51* (p. 184) shows the median *Housing Costs As a Percentage of Income* (HCAPI) for all and renter-end units for units based on their affordability classification (e.g., upward or downward filtered) for each measure. This table also delineates how outcomes vary by the ethno-racial characteristics of the final occupants.

Starting with the repeat income measure (top of *Table 51*), median HCAPI is much higher for occupants of units that filtered down (35.5%) than for occupants in units that filtered up (20.4%). When narrowed to renter-end units, this divide widens further with median HCAPI of 23.2% and 43.2% for upward and downward filtered units, respectively. When looking at the HCAPI for Black and Hispanic/Latino households compared to all others, differences widen even further. Black and Hispanic/Latino renters have a median HCAPI of 25.1% in upward filtered units and 47.7% in downward filtered units compared to 22.1% and 38.7% respectively for all other households. Essentially, occupants of units that “filtered down,” as identified by changes to repeat incomes, pay much more for housing relative to their incomes and Black and Hispanic/Latino households pay a premium on top of that. While these numbers may feel extreme, particularly for Black and Hispanic/Latino households, over a quarter of Black and Hispanic/Latino renters are severely rent-burdened and pay over 50% of their incomes towards housing costs (Wedeen, 2021).

Table 51: Median Housing Costs As a Percentage of Income (HCAPI) by measure, race/ethnicity, and tenure

<i>Repeat Income</i>	<i>All households</i>				<i>Black and Hispanic/Latino households</i>				<i>non-Black or Hispanic/Latino households</i>			
	<u>All units</u>		<u>Renter-end units</u>		<u>All units</u>		<u>Renter-end units</u>		<u>All units</u>		<u>Renter-end units</u>	
	<i>Median HCAPI</i>	<i>se</i>	<i>Median HCAPI</i>	<i>se</i>	<i>Median HCAPI</i>	<i>se</i>	<i>Median HCAPI</i>	<i>se</i>	<i>Median HCAPI</i>	<i>se</i>	<i>Median HCAPI</i>	<i>se</i>
Upward Filtered	20.4%	0.2%	23.2%	0.3%	22.8%	0.4%	25.1%	0.6%	19.4%	0.2%	22.1%	0.4%
Downward Filtered	35.5%	0.4%	42.3%	0.6%	43.2%	0.7%	47.7%	0.9%	32.5%	0.4%	38.7%	0.7%

<i>Gross Rent Threshold</i>	<i>All households</i>				<i>Black and Hispanic/Latino households</i>				<i>non-Black or Hispanic/Latino households</i>			
	<u>All units</u>		<u>Renter-end units</u>		<u>All units</u>		<u>Renter-end units</u>		<u>All units</u>		<u>Renter-end units</u>	
	<i>Median HCAPI</i>	<i>se</i>	<i>Median HCAPI</i>	<i>se</i>	<i>Median HCAPI</i>	<i>se</i>	<i>Median HCAPI</i>	<i>se</i>	<i>Median HCAPI</i>	<i>se</i>	<i>Median HCAPI</i>	<i>se</i>
Not Affordable (Final Year)	28.2%	0.2%	33.4%	0.4%	32.8%	0.5%	36.0%	0.7%	25.8%	0.3%	31.0%	0.6%
Affordable (Final Year)	17.5%	0.3%	26.0%	0.9%	19.8%	0.4%	28.4%	1.0%	16.2%	0.3%	22.3%	1.4%

Unsurprisingly, the gross rent measure's outcomes are vastly different in comparison. Since this measure identifies affordability based on rent level, it is not surprising that median HCAPI is lower for affordable units in general (17.5%) than unaffordable units (28.2%). Median HCAPI for renters in affordable was higher nominally (26.0%) but still lower than median for unaffordable units (33.4%). There is one way in which the gross rent results are similar to the repeat income results—Black and Hispanic/Latino renters have even higher median HCAPI estimates, 28.4% for affordable units and 36.0% for unaffordable units.

Overall, these results seem to indicate that the gross rent measure is fairly effective at identifying units that are actually affordable to the households that occupy them. However, while negative changes in repeat incomes definitely indicate that lower-income households occupy those units, these same households are likely to pay much higher shares of their incomes to occupy those units. Researchers have found amongst these households, there are often specific behaviors utilized to survive their affordability issues, including cutting back consumption, working more hours, and altering their homes to accommodate more occupants (Angst, Rosen, De Gregorio, et al., 2025). Therefore, this measure may obfuscate important conditions and context for these occupants beyond even issues like inadequacy issues or neighborhood quality

6.7 Conclusions

The primary research question guiding the analyses in this chapter was whether BIPOC and low-income renters receive similar benefits from filtering as other households or if distributional impacts are uneven. In addition to providing descriptive data, which indicate that Black and Hispanic/Latino as well as low-income renters are more likely to end up in affordable units (for both measures), several regression analyses were done in order to unwind some of the systemic differences in incomes across ethno-racial groups. These analyses included some rudimentary controls for unit and neighborhood quality, whether units were located in gentrifying neighborhoods, CBSA-level supply and cost trends, etc.

The resulting evidence indicated that filtering outcomes vary by both income levels and race/ethnicity. For low-income households, this means it is far more likely that they end up in NOAH units than high-income households. This is true for both measures—households from the first income decile have lower incomes than previous households in nearly 90% of the units that they occupy in the final year compared to about 15% of households in the tenth income decile. On the other hand, over 40% of units occupied by households in the first decile are affordable in the final year at the 50% of AMI level compared to just over 10% of units occupied by households in the tenth income decile. *Table 52* (p. 189) shows a detailed overview of these outcomes for both affordability measures.

As mentioned previously, descriptive data show that filtering varies across both income and race/ethnicity. Due to systemic differences in incomes across ethno-racial groups, evaluating filtering outcomes across ethno-racial groups requires this to be considered. In fact, descriptive data for the repeat income measure reveals that within decile and quartile differences exist across ethno-racial groups but in the opposite direction of what is observed overall. While *Tables 41*

and 42 (p. 167) show Black and Hispanic/Latino occupied units filtering downward more prominently on average using the repeat income measure, these groups generally have slower downward filtering within household income quartiles/deciles (*Table 48*, p. 170). While a larger proportion of first income quartile Black and Hispanic/Latino households live in units that have filtered downward compared to White, non-Hispanic households, a larger proportion of these households also live in units that have filtered upward. Regardless, the regression outputs provide more even comparisons given that those households are also unevenly distributed nationally, with BIPOC populations increasingly more concentrated in major metros compared to White, non-Hispanic populations (Frey, 2022).

However, it is worth noting that these data may simply indicate differences in housing quality as lower deciles also have higher rates of unit inadequacy issues and higher rates of low neighborhood ratings. Systemic differences in incomes across ethno-racial groups also makes the cause of variation difficult to unwind. As a result, regression analyses evaluated how filtering varied across these groups while controlling for important factors (unit inadequacy, market trends, etc.) influencing filtering outcomes.

Both measures revealed that low-income, Black and Hispanic/Latino households seem to have measurably different outcomes for both measures compared to all other households. Specifically, the repeat income model indicated that low-income, Black and Hispanic/Latino households have repeat incomes that are about 16 to 18% higher than other low-income households occupying similar units, depending on the model specification. Using fairly conservative assumptions, low-income Black and Hispanic/Latino renters are between 5 and

43% *less* likely to attain unsubsidized housing that is affordable to extremely low-income⁹² households compared to other low-income households when controlling for various other household, housing market, unit, and neighborhood characteristics.

These results seem to align with the first two hypotheses discussed in 6.4, with BIPOC households both generally being more likely to live in units identified as downward filtered in general (based on descriptive data) and also having a more difficult time in attaining occupancy in NOAH units compared to other low-income households. Seemingly, accessing NOAH units involves similar challenges and inequities that persist in other housing-related outcomes for low-income, Black and Hispanic/Latino households in particular.

Lastly, this chapter aimed to better understand how affordable downward filtered units actually are to their occupants. Understanding how these outcomes vary between the two measures (repeat income and gross rent threshold) is important as well since little past comparison has been done on these two commonly used measures. When housing costs relative to household income were quantified amongst units identified as affordably by these two measures, the results provided interesting context for how some of these outcomes ought to be considered. Specifically, the percentage of incomes used on housing were much lower for units designated as affordable at the 50% of AMI threshold compared to other units. That said, Black and Hispanic/Latino households still paid a greater share of their incomes to reside in these units. The units identified as having filtered downward using the repeat income measure (i.e., had negative change in repeat real incomes) had results indicating the opposite. Specifically, units with negative changes in repeat incomes had occupants paying much higher shares of their

⁹² Extremely low-income is defined as incomes equal to 50% of HUD's Area Median Income

incomes on housing costs than other groups. Again, Black and Hispanic/Latino households paid even larger shares of their incomes on housing compared to other households. This is important because it both further affirms the persistent differences in outcomes experienced by Black and Hispanic/Latino households and the limitations to using the repeat income measure alone as a measure of (shifting) affordability.

Table 52: Filtering outcomes by final year income decile; repeat income and gross rent, all units

<i>Income Decile (Final Year)</i>	<u>Repeat Income</u>	<u>Gross Rent Threshold</u>			
	<i>% Downward Filtered</i>	<i>AU</i>	<i>AA</i>	<i>DF</i>	<i>UF</i>
1	89.61%	44.27%	20.67%	23.20%	11.86%
2	73.22%	52.21%	17.41%	19.25%	11.13%
3	65.52%	59.40%	12.56%	16.50%	11.54%
4	58.44%	65.44%	9.08%	13.54%	11.95%
5	48.74%	65.80%	8.68%	12.16%	13.36%
6	46.48%	69.26%	5.71%	14.74%	10.30%
7	39.42%	74.04%	4.90%	8.57%	12.50%
8	36.68%	74.74%	3.49%	9.25%	12.53%
9	27.51%	74.83%	3.27%	9.28%	12.63%
10	15.32%	77.26%	3.18%	8.53%	11.03%

6.8 Discussion

The results from these analyses are not necessarily straight forward, particularly since there are systemic differences between ethno-racial groups, including but not limited to spatial concentration, income levels, and even discrimination in the housing market (Christensen et al., 2021). That said, both descriptive data and regression outputs consistently show variation between ethno-racial groups.

While the regression outputs indicate that Black and Hispanic/Latino renters may have more obstacles in attaining NOAH compared to other households, there are several areas that

warrant further investigation. In particular, Black and Hispanic/Latino households are more likely to be renters, live in units with adequacy issues, live in major metro areas, occupy rent stabilized units, occupy units with more bedrooms⁹³, and live in overcrowded housing⁹⁴. The models utilized also have endogeneity issues similar to other quantitative analyses of filtering—supply and cost shifts are closely related and understanding their specific impacts on filtering and disparities is difficult to delineate. For example, increased supply, as measured by growth in overall housing units, is correlated with slower filtering.

Intuitively this makes sense—markets with the highest home prices and rents are likely those with the most unmet demand and therefore more likely attract the development even if they have more restrictive zoning and land use regulations. Interestingly, the supply elasticity variable had differing impacts between the repeat income and gross rent measures. A more responsive housing supply (i.e., higher supply elasticity) is associated with increased likelihood of a unit being affordable at the 50% of AMI threshold while also being associated with higher repeat incomes. This is not necessarily inconsistent, as it could simply indicate that more supply elastic housing markets both attract (or retain) higher income households and free up more deeply affordable housing units.

That said, further investigation into how housing market conditions independently impact low-income and Black and Hispanic/Latino households would need to be done to draw more definitive conclusions. While these households are unevenly distributed across metro areas (and urban versus rural), they are also spatially concentrated within those areas. These analyses

⁹³ Author-compiled data from both samples used in this study; while Black and Hispanic/Latino households on average lived in units with more bedrooms, these households are also more likely to live in overcrowded units. Also, the gross rent method determines affordability based on the number of units in a bedroom.

⁹⁴ See: Airgood-Obrycki, W. (2020, June 8). High-Proximity Jobs and Household Vulnerabilities. *Housing Perspectives*. <https://www.jchs.harvard.edu/blog/high-proximity-jobs-and-household-vulnerabilities>

included some controls (gentrifying tracts, neighborhood rating, unit quality, etc.) that allude to these differences, more precise neighborhood-level controls could further illuminate the relationship between market characteristics and household/housing-unit level outcomes. What can be definitively said is that filtering outcomes are similar to many other housing outcomes in that variation along ethno-racial and economic characteristics is evident.

This chapter specifically evaluated how these groups are differentially experiencing outcomes in the market-rate housing market. In the U.S. this sector of the market is critically important since most of the country's affordable housing stock is NOAH and is not receiving any direct subsidy. Thus, low-income renters are deeply reliant on this housing stock and the fact that ethno-racial disparities are reproduced amongst these units, while unsurprising, ought to be of deep concern to policymakers, legislators, housing developers, all levels of government, and anyone with an interest in advancing equity and alleviating the housing crisis should be concerned about these implications. Low-income, Black and Hispanic/Latino renters are particularly vulnerable in high-cost markets, the same areas where they are most concentrated. That said, low-income households and renters are vulnerable in general, so identifying targeted ways to address these ethno-racial disparities is likely to be of value to all households struggling to find stable, high-quality affordable housing in high-cost housing markets.

CHAPTER 7: Conclusion, Limitations, and Policy Implications

This dissertation has evaluated filtering dynamics in the United States from 2015 to 2023 in order to better understand when filtering is more or less prominent, sources of variation in filtering, and a detailed understanding on the state of Naturally Occurring Affordable Housing in the U.S. during this time period. The first section in this chapter (7.1) outlines the conclusions made based on the findings in the various analyses throughout Chapters 4, 5, and 6. The following section (7.2) describes how these findings could inform and strengthen housing policy and improve affordability outcomes, particularly for low-income, BIPOC communities in the United States who lack access to subsidized housing options. Lastly, (7.3) discusses possible areas for future research, including outstanding questions that should be answered in order to provide more clarity on the causal mechanisms driving the observed results.

7.1 Conclusion

Housing affordability is a mounting challenge and has become a salient policy issue in the United States. Even a deeply ideologically and politically divided Senate has recently proposed widely supported bi-partisan legislation that would both address housing supply obstacles and prohibit corporate investors from accumulating single-family homes, theoretically improving access to homeownership for households. In fact, racial equity concerns are part of the motivation for this bill, as articulated by Republican Senator Tim Scott. This type of proposal is fairly uncommon for federal lawmakers, particularly since most decisions tied to housing production are made locally. However, major housing policy proposals and laws have been enacted in places like California, Minnesota, Oregon, and numerous localities in those and other states.

Baked into many of these reforms is an acknowledgement that market-rate housing remains the primary source of affordable housing in the United States. Arguably the primary reason that increasing housing supply has been so widely supported by those seeking to improve housing affordability is the theory that older units eventually “filter down” to lower-income households. As outlined in *Chapter 2 (section 2.1)*, researchers have generally found evidence supporting this phenomenon. However, despite evidence that various housing outcomes are impacted by ethno-racial characteristics, even within low-income groups, there is little research on how similar types of disparate impacts might exist in the filtering process. In particular, there is limited understanding of how accessible NOAH housing units are for low-income and BIPOC families seeking affordability without access to subsidized housing.

A longitudinal panel was created using the American Housing Survey (AHS) that allows for units to be observed over the time period of the study (2015 to 2023), with data collected on the same housing units every other year. Thus, changes to rents, household incomes, tenure, and numerous other unit and household characteristics were tracked over time. The use of two different measures for affordability, repeat income and gross rent threshold, allow for a more nuanced understanding of affordability. The repeat income measure evaluated changes in real income over time, which can then measure whether incoming households are lower-income compared to the initial occupants, indicating a unit has filtered downward to a lower-income family, or not. On the other hand, the gross rent threshold measure evaluates whether a given unit is affordable at HUD’s 50% of AMI threshold or not. Importantly, this measure captures whether a unit’s rent is a relatively affordable or not rather than simply indicating how household incomes have shifted. Given recent trends of renters paying increasingly higher proportions of their incomes to rents, this measure provides further context around whether units are filtering

downward into affordable rent levels or not. Taken together, these measures provide useful context about the state of NOAH across the U.S., including the contexts where filtering is more or less prominent and what factors might be driving these differences.

Chapter 4 took the broadest look at filtering, quantifying the number of units that filtered down nationally during the study period. In general, this analysis showed that market-rate units were generally filtering upward during the study period, with only an estimated 48.9% of units filtering downward and mean repeat incomes increasing by 16.6% nationally. This finding aligns with Spader’s (2024) findings for a similar time period (2015 to 2021). Amongst the sample of units analyzed, there was also an upward shift in the share of owner-occupied homes, which could explain some of this upward trend—specifically if more high-income renter households purchased homes during this period of time than normal, the data could be biased by more turnover amongst high-income households. That said, the specification that restricted analysis to units with multiple turnovers during the study period while being much lower (+8.9% mean change in repeat incomes), was still positive and showed units to be generally filtering upward. The gross rent threshold of 50% of AMI showed that the number and share of affordable rental units was fairly constant during this time period, though there were large increases to HUD income levels during this period of time as well, particularly in large cities like New York City and Los Angeles.

Other important findings from this chapter included filtering rates and unit age had a non-linear relationship, with downward filtering increasing for units until they reach 70 to 80 years of age when downward filtering begins to slow with units older than that having lesser magnitude but still negative estimates for repeat incomes⁹⁵ and stronger odds of being affordable at the 50%

⁹⁵ The impact from unit age would not reach 0 until a unit were aged ~155 years based on this formula, though this dataset does not identify units any older than 104 years of age (i.e., 1919 is the earliest value for the year built variable).

of AMI threshold⁹⁶. Regardless, it seems that older units do generally filter downward more prominently though “survivor bias” (i.e., the removal of lower quality units over time leading to better quality units remaining amongst older units) may be one of the factors causing downward filtering to plateau. Additionally, a top-coded HUD inadequacy measure had a greater impact on filtering outcomes for renter-occupied units than neighborhood ratings, which runs counter to prior findings that neighborhood- and city-level indicators were bigger determinants of filtering outcomes than individual unit characteristics (Sommerville and Holmes, 2001). Interestingly for both measures, the binary variable that indicated whether a unit had a gut rehabilitation did not have significant impacts on affordability⁹⁷. Some descriptive data shows that affordable units (gross rent threshold) are more likely to be demolished and removed in general compared to units that are not affordable and that both rental and inadequate units (both samples) are more likely to be removed from the housing stock.

Chapters 5 and 6 went deeper by investigating how filtering variation relates to unit- and household-characteristics while also controlling for housing market (i.e., CBSA-level) trends. *Chapter 5* showed repeat incomes increasing in most geographies across the U.S. (i.e., upward filtering) while the gross rent measure showed a large number of units downward filtering and becoming affordable at the 50% of AMI level. However, the latter finding is largely driven by HUD’s “High Housing Cost Adjustment” in cities like New York City, Los Angeles, and San Francisco, which incidentally also have large numbers of rent-regulated housing units that may have become affordable merely by nature of the HUD threshold being adjusted substantially upward⁹⁸. Still, the West and Northeast regions of the U.S. still show higher growth in repeat

⁹⁶ For this measure, estimated impacts from age do not reach 0 until ~140 years

⁹⁷ While not included in this chapter, there was a specification that included a *MaxRehab*Renter (base year)* interaction term that indicated units initially occupied by renters that also were rehabbed had strong upward swings in repeat incomes

⁹⁸ This upward adjustment is not necessarily bad for affordability, as it upward adjusts FMRs, making market-rate housing more accessible to voucher holders. However, this adjustment in specific geographies may be impacting some observed outcomes.

incomes, matching outcomes from prior research (Liu et al., 2021; Rosenthal, 2014; Spader, 2024).

When evaluating CBSA-level supply and demand indicators, the repeat income measure was more sensitive to changes in housing supply and levels of land use restrictiveness (as measured by the WRLURI variable) while the gross rent measure was sensitive to both supply and demand indicators, depending on the specification. For the renter-end specification, affordability was most sensitive to changes in CBSA-level housing costs as opposed to baseline costs or supply changes. These outcomes seem to generally align with what scholarship has already indicated—downward filtering of units that are affordable to very low-income households is much slower in high-cost housing markets while units in cities with more limited supply and restrictive land use regulations are more likely to have more prominent growth in repeat incomes. The implications are slightly different, though closely related—more responsive housing supply seems to create enough competition to reduce relative growth in real incomes between transitions while a unit’s affordability in terms of rent level is more impacted by local housing cost trends. To further evaluate local conditions, the impacts of gentrification were also evaluated based on tract-level characteristics.

Compared to units in higher income areas (i.e., *non-gentrifiable* tracts), units in both *gentrifying* and *not gentrifying* neighborhoods have lower repeat incomes, though repeat incomes are indeed higher (23 to 27%) for units on *gentrifying* tracts compared to those on tracts that are *not gentrifying*. However, in terms of its impact on units affordable at the 50% of AMI threshold, units on *gentrifying* tracts are actually more likely to be affordable in the final year than units on tracts that are *not gentrifying*. Importantly, *gentrifying* tracts are concentrated in larger CBSAs, CBSAs with more growth in housing units, and have a higher proportion of units that are

affordable in the base year than tracts on both *non-gentrifiable* and *not gentrifying* tracts. While these characteristics are controlled for, there may be other tertiary policies or characteristics that are also present in these areas—stronger tenant organizing, local policies/programs that support long-term residents in gentrifying areas, etc. Regardless, this chapter revealed that there is clear evidence that filtering and affordability outcomes have fairly distinct outcomes depending on associated spatial characteristics.

Chapter 6 shifted focus to how filtering varies based on household characteristics, namely ethno-racial and socioeconomic characteristics. Initially, filtering outcomes seem to be consistently better for Black and Hispanic/Latino households for both measures. However, systemic differences in incomes likely are impacting both measures—lower overall incomes mean repeat incomes are lower for units occupied by those groups, and it is also likely that low-income households are also more concentrated in affordable units. When evaluating how outcomes for Black and Hispanic/Latino households varied compared to other households, a regression was run that controlled for the aforementioned housing market characteristics, unit characteristics (e.g., inadequacy), etc.

For both measures, the results indicate that Black and Hispanic/Latino households may face obstacles in accessing NOAH units. By using an interaction term between a binary variable indicating whether a unit was occupied by Black or Hispanic/Latino household in the final year and another binary variable for whether the final occupant was in the first CBSA-level income quartile in the final year. The results indicate that low-income BIPOC households have repeat incomes that are 16 to 36% higher than other low-income households. Similarly, low-income BIPOC renters are between 5 and 43% less likely to attain unsubsidized housing that is affordable at the 50% of AMI threshold.

Interestingly, the supply elasticity variable had a positive relationship with both the repeat income and gross rent measures, indicating that more elastic local housing supply both positively impacted repeat incomes and increased odds of a unit being affordable at the 50% of AMI threshold. While this may seem contradictory, it may provide a bit more context of how supply shifts impact local affordability. Specifically, if increased supply both attracted higher-income households and provided supply that attracted existing higher-income households, it is reasonable to expect that both repeat incomes rise (due to higher-income households moving into new units) and existing affordable units becoming more accessible to low-income households via “vacancy chains” as described by Mast (2023). While further investigation is needed to affirm this causal change, it seems like a plausible explanation to what may seem like contradictory surface-level results.

Lastly, housing costs burdens were evaluated in order to understand how the two measures of affordability relate to actual costs burdens experienced by households. In general, the units identified as affordable by the gross rent method are actually affordable (i.e., housing costs are less than 30% of household income) whereas units identified as downward filtered by the repeat income typically had *higher* average housing costs relative to incomes. For both measures, both renters and Black and Hispanic/Latino households had higher cost burdens than other households. Therefore, the gross rent measure seems to be more accurate in identifying units actually affordable to occupants.

7.2 Policy implications

As mentioned throughout this analysis, there are a lot of possible endogeneity issues endemic to identifying sources of filtering variation. Each housing market has deeply unique contexts—from local policies, zoning regulations, political environments, and other characteristics that are difficult to account for. That said, the results of the analyses outlined in Chapters 4 through 6 reveal outcomes that are worth contemplating, especially given the pervasiveness of housing affordability challenges throughout the U.S. Specifically, nearly every one of the fifteen largest U.S. cities that are included in the AHS’s integrated national sample are experiencing upward filtering of housing units in general with all Census Divisions and twelve of the aforementioned fifteen cities all showing that units are generally filtering upward⁹⁹.

To start, certain types of units are more likely to filter downward or otherwise remain or become affordable over time. In Chapter 4, descriptive data shows that repeat incomes are lower in certain types of tenure shifts, specifically they are only negative on average in instances where the first and last households are renters. Other types of tenure shifts (i.e., owner to owner, renter to owner, or owner to renter) have positive mean repeat incomes, meaning those units are on average filtering upward. Similarly, downward filtering is more prominent amongst older units (though it plateaus to some extent amongst units over 70 years of age), units with adequacy issues, and units in neighborhoods that receive lower ratings in quality by occupants. Impacts to filtering can also vary by tenure—renters are generally less sensitive to neighborhood quality as compared to homeowners, for example.

Regardless, the variations of these outcomes should shape any housing policy meant to preserve and/or expand the NOAH stock in the U.S. In particular, preserving existing rental

⁹⁹ See *Table 18* on p. 111 for more details

units as rental units would help facilitate downward filtering generally. There are notably many challenges facing existing NOAH, including high levels of rent burden, inadequacy issues, access to financing, and effectively both encouraging and efficiently regulating private investors that build and maintain (or do not maintain) these units (DiPasquale & Cummings, 1992; Hipp et al., 2025; MacDonald, 2012). The value of low-cost capital was evident for homeowners during the study period, with monthly payments falling by an average of \$279 for homeowners who refinanced when interest rates were at historic lows during the COVID-19 pandemic, though BIPOC homeowners were less likely to do so (Gerardi et al., 2021) and BIPOC renters were at higher risk of eviction during this same time period (Wedeen, 2021).

That said, there are effective preservation and financing strategies that have been effective both in the U.S. and in other countries that policymakers should evaluate and consider deployment of, including municipal programs to acquire and rehabilitate housing units or provide financial incentives for owners to do so as well as expanded tenant protections that have shown early signs of success in keeping renters in privately-owned rental units (Akinsulire et al., 2024; Chapple et al., 2023). Typically, programs that finance rehabilitation have the added benefit of moving those units into some form of long-term rent restriction, preserving affordability over the long-term. Similarly, units that shifted from renters to homeowners had very high upward swings in repeat incomes, indicating sharp upward filtering rates. Conserving rental units could be done not just via financing, but through policies that prevent conversion of rental units into condominium units. There was also some evidence in the data that many owner-occupied units were affordable at the 50% of AMI threshold, possibly indicating that homeownership could be a pathway towards long-term affordability. Thus, programs like Washington DC's Tenant Opportunity to Purchase Act when paired with condo conversion

restrictions could both generally preserve existing rental units while also facilitating long-term affordability via homeownership opportunities in cases where buildings and/or units are converted from rental units into condominiums. In fact, the evidence presented in *Chapter 4* may be useful in identifying *when* existing units should be targeted for these types of programs. Specifically, downward filtering seems to be occurring for these units for the first 50 to 70 years of age before plateauing. This period may be the most effective time to deploy refinancing, acquisition, or other policies to extend or retain their affordability.

In terms of spatial variation in filtering, *Chapter 5* revealed some interesting trends. While nearly every U.S. city in the national sample¹⁰⁰ is experiencing upward growth in repeat incomes, indicating that units are generally filtering upward in large cities during the 2015 to 2023 time period, there were some large cities that experienced prominent downward filtering when using the gross rent measure. As described in that chapter, this seems to be driven by two factors: (1) HUD’s “High Housing Cost Adjustment” was higher in large CBSAs and (2) many of these same cities have large amounts of rent regulated, unsubsidized housing units. While this likely needs further research in order to be more clearly understood, it does lend some credence to the fact that rent regulations can help keep units affordable over time. In this case, HUD rent adjustments rose more prominently than rents did during this time, even though these cities (New York City, Los Angeles, and San Francisco) had some of the most expensive housing costs in the country. *Table 22* in *Section 5.6.2* (p. 11) showed that these same cities both had prominent amounts of rent controlled units (approximately 560,000 units combined within the sample), and those units were more generally more likely to end as affordable compared to non-rent-controlled units. While not definitive, these outcomes appear to lend credibility that rent-control

¹⁰⁰ This is limited to the 15 largest CBSAs in the U.S. See *Section 3.1.1* for a detailed list of these CBSAs.

policies aid in both the preservation and creation (i.e., downward filtering) of housing affordability amongst existing units. This could be a low-cost way to preserve housing affordability amongst existing housing units, especially considering the evidence that rent control policies, particularly when they exempt newly constructed units, typically do not impact housing production (Pastor et al., 2018).

The latter sections of *Chapter 5* showed evidence of increased housing supply generally being associated with lower repeat incomes while more restrictive local land use regulations were associated with higher repeat incomes. When running a similar regression on renter-end units only, similar outcomes were observed only with renters' outcomes being even more sensitive to changes in housing units and land use regulations. The gross rent sample's outcomes varied slightly, showing that rental units were more sensitive to CBSA-level changes to housing costs, even more so than baseline housing cost levels (though those also significantly impacted outcomes). Contrary to some of the descriptive data outlined in this chapter, this outcome indicates that downward filtering is actually slower in high-cost housing markets, particularly those with more growth in rent levels in recent years when controlling for other variables. At a more granular level, outcomes also showed variation across neighborhood types (*gentrifying*, *not gentrifying*, and *non-gentrifiable*) with *gentrifying* areas having higher repeat incomes than other low-income areas that were *not gentrifying*. However, units on *gentrifying* tracts were more likely to end as affordable compared to units on *not gentrifying* tracts when using the gross rent threshold measure. This requires further investigation but does at least clarify that neighborhood change and relative levels of affluence impact filtering outcomes. Thus, strategies to induce increased filtering likely will have different outcomes, depending on where they are applied (e.g., what types of housing markets or neighborhoods). High-cost cities with more intense cost

pressures have a clear justification for pushing for policies that induce more housing production and loosen local regulations that are negatively impacting production. However, units are less likely to be affordable to very low-income households in areas with more housing production, so preservation strategies like affordable financing for rehabilitation in exchange for long-term affordability commitments as well as policies that strengthen tenant rights (right to counsel, just cause evictions, rent control, etc.) may be necessary to prevent the loss of the most affordable portions of the NOAH stock.

Chapter 6 focused on how variation is experienced across ethno-racial and socioeconomic groups. While the descriptive statistics showed low-income and BIPOC households seemed to have more access to NOAH compared to White, non-Hispanic households, inclusion of dummy variables (and an interaction term) for both low-income and Black or Hispanic/Latino households into the regression model revealed that low-income BIPOC households have both higher repeat incomes and lower odds of residing in affordable units compared to other low-income households. Taken along with what was revealed in *Chapter 5* regarding specific pressures on affordable units, low-income BIPOC households may face unique challenges in accessing NOAH compared to other renters and may be particularly vulnerable to changing local conditions. This measurable reality should further guide policymakers by not only considering local market conditions, but also which households and neighborhoods might be most sensitive to them. While some of the aforementioned policies can be expensive to implement universally (e.g., right to counsel), it would make sense to specifically target communities that are most vulnerable challenges in acquiring NOAH with appropriate policy interventions. In particular, there is evidence that right to counsel strategies, even means tested applications, have been successful at mitigating evictions. There is also

evidence that a large share of evictions derived from small sums of unpaid rent, which means targeted rental assistance programs could also aid low-income and, in particular, low-income BIPOC renters who face persistently higher rates of eviction (Chapple et al., 2023; Harrison et al., 2021; Preston & Reina, 2021).

While the variation in outcomes across race and socioeconomic class highlight persistent inequality that ought to be addressed by policymakers when deploying interventions if these inequities are to be addressed, the need to expand housing supply in many contexts is still very much relevant to the challenges facing renters and low-income and BIPOC renters in particular. The interaction terms from the outputs in *Chapter 6* revealed that Black and Hispanic/Latino households were uniquely impacted by changes in housing supply, with repeat incomes being lower for those households in CBSAs with higher rates of unit supply growth. While the likelihood of their unit being affordable at 50% of AMI was reduced with increases to supply growth, they were also more sensitive to CBSA-level rental cost growth rates, meaning higher cost growth more negatively impacted these households in particular. Thus, while there is some evidence of negative impacts from increased development activity, these groups are also more deeply impacted by low-supply, high-cost markets than other low-income households.

Additionally, supply elasticity variable had a positive relationship with both the repeat income and gross rent measures, indicating that more elastic markets increased the likelihood a unit had affordable rent and that repeat incomes increase in general. This could be driven by vacancy chains and sorting processes whereby higher income households occupy newly constructed units while simultaneously allowing existing units to filter down (Mast, 2023; Pastor et al., 2018), though ethno-racial disparities still would persist based on the model outputs. Thus, targeted strategies to grow housing supply may be justified in order to both improve affordability

generally and address persistent ethno-racial inequities in outcomes. Specifically, increasing access to better transit, jobs, and neighborhoods might be useful in both mitigating possible direct negative impacts in gentrifying or low-income neighborhoods and closing other equity gaps derived from exclusionary land use practices. Still, developing quality, affordable housing in low-income communities will also require land use reforms though more concerted anti-displacement policies could be paired with supply incentives to both retain residents and develop desperately needed affordable housing to provide future stability.

7.3 Limitations

There are several limitations to this study that are worth noting. To start, there are fairly substantial differences between the single turnover and multiple turnover subsamples of the repeat income sample, so the pooling of these observations makes the results in this study inappropriate comparison points to other studies that narrow their observations to those with multiple turnovers. While the pooling of data was an intentional design choice¹⁰¹, it still includes a different universe of housing units than other studies have evaluated. This may be part of the reason repeat incomes look particularly high in a few specific housing markets (Los Angeles, New York City, Philadelphia, and Boston), particularly amongst owner-occupied units, though further investigation into those outcomes also warrants further review of the measure and these specific outcomes. Given results were not generally aggregated or calculated at the CBSA-level and most results focused on renter-end units, this is likely less of an issue as it relates to model outputs, but still worth noting and acknowledging possible systemic differences in the sample used here versus those used by prior researchers who utilized this method.

¹⁰¹ Whether a given unit has one or multiple turnovers during the study period does not preclude it from being part of the NOAH stock or having shifting affordability, so excluding these units would have arguably undermined the purpose of this study.

Additionally, while this study initially planned to remove LIHTC units to more accurately identify NOAH units, accurately identifying these units within the AHS dataset was not possible with the data that was utilized. The inclusion of these units likely would bias outputs in a conservative manner where units identified as NOAH units having some chance of actually being subsidized. Given that national trends during the study period showed that downward filtering was quite slow, the reality may be even more challenging as it relates to the NOAH stock in the U.S.

For the gross rent measure, there was a lot of variation in HUD rent level adjustments during the study period. In fact, the 30% of AMI calculation was completely altered in the middle of the study period, which is in part why that threshold was not included as well. A control for the magnitude of HUD rent adjustment was included for the analyses in Chapter 6, but otherwise outputs were biased by systemic differences in HUD rent adjustments—particularly cities that had High Housing Cost Adjustments saw the 50% of AMI rent level increase much more relative to other cities. While this theoretically put their Fair Market Rents (FMRs) more in line with actual market rents in those cities, it definitely obfuscated the results presented in *Chapters 4 and 5* using this measure.

Perhaps most importantly, some of the observed variation in outcomes that is attributed to unit or household characteristics may actually be due to spatial differences that are not fully accounted for in the models used. For example, Black and Hispanic households are spatially concentrated within the United States, with half of the U.S.'s Black population residing in the South (Martinez & Passel, 2025) while Hispanic/Latino households are concentrated in the West and Southwest (Frey, 2019). While there are CBSA-level controls for relative housing cost levels, changes in housing costs, HUD rent growth, changes to housing supply, and supply

elasticity, there could be other unobserved spatial differences that are driving variation and simply correlate with the regions where these households are (or are not) spatially concentrated. That said, trying to disentangle such relationships is a common issue in this type of research—establishing a clear counterfactual for a given housing market is impossible given how distinct each region, state, and city is from one another and how important these distinctions are to housing costs. Thus, the outputs in Chapter 6 in particular are more accurately describing how outcomes vary across the described groups but fall short of identifying any sort of causal relationship or a causal mechanism that is driving these observed differences.

Thus, the outputs derived from the models in this study should be received primarily as descriptive data. What can be said was that measurable differences were observed for Black and Hispanic households using two different affordability measures in models that included various controls for unit, housing market, neighborhood, and household characteristics. However, causal links were not clearly identified nor should model outputs be viewed as proof of any causal relationships. As is described in the next section (*7.4 Areas for future research*), more granular spatial analysis would help strengthen prospective claims about differences across ethno-racial groups or other demographic groups.

Outside of these endogeneity-related issues, this subset of data is collected across a relatively small window of time (2015 to 2023) that also had a significant exogenous shock (the 2020 global pandemic) that impacted housing trends, interest rates, evictions, and numerous other housing-related variables. The growth in homeownership and high rates of refinancing during this time period felt fairly evident in the data, for example. A longer-term panel of data would be more ideal to minimize bias from a single shock like a global pandemic and would

expand the number of observations with multiple turnovers that could also help provide more precise estimates since more change would be observed across the study period.

To summarize, the outputs described in this study should be viewed as descriptive and directional in most cases. The pooling of data and rudimentary controls were meant to describe broad categories of possible variation in filtering. To more meaningfully understand how (and if) specific subgroups are differentially impacted as well as what causal mechanisms are driving possible differences, more granular spatial analysis (or the inclusion of more specific spatial controls) would be necessary to draw more definitive conclusions.

7.4 Areas for future research

While the findings outlined thus far have important implications, they also lead to numerous partially or fully answered questions that warrant further investigation. To start, while some broad descriptive data revealed that inadequacy, unit age, and downward filtering are all linked, the specific conditions and long-term outcomes (e.g., demolition, conversion, or rehabilitation of a poorly maintained affordable unit) that tie these factors together should be further investigated. Particularly in light of recent research that shows affordable, at-risk housing stock is also associated with high rent burdens (Hipp et al., 2025), better understanding how units shift into becoming inadequate and the nature of their lifecycle could be helpful in understanding how important these units are to the NOAH stock in the U.S. and the best strategies to preserve them. Importantly, descriptive data in *Chapter 4* also indicates that affordable units are twice as likely to be demolished or otherwise removed from the housing stock than units that are not affordable at 50% of AMI and renter-occupied units that are rehabbed see sharp upswings in repeat incomes. Similarly, units occupied by renters and units that were inadequate were both

more likely to be removed while units occupied by voucher holders were less likely to be removed. Regardless, further understanding the causal mechanisms (e.g., poor financing options or more profitable uses for the property) is necessary to formulate the best strategy at preserving these units as affordable over the long-term.

While *Chapter 5* provides useful measures of how certain housing market conditions and spatial differences (e.g., gentrification, neighborhood quality) relate to filtering variation, more granular spatial impacts should be evaluated as well. Outside of the gentrification analysis, primarily CBSA-level impacts were measured and evaluated. While some research has pointed to the importance of CBSA-level factors and the geographic spread of vacancy chains associated with filtering (Mast, 2023; Sommerville and Holmes, 2001), better understanding within-CBSA variation and the impact of more local housing market trends would be worth further investigation. Particularly, understanding how these trends impact low-income and BIPOC renters may be better understood through this lens, especially considering how these households often are spatially segregated within cities. Furthermore, recent research has found evidence that income growth and economic factors are driving shifts in home and rent prices, not local supply conditions (Louie et al., 2025). To a similar end, the gentrification analysis revealed that units on gentrifying tracts are more likely to remain at affordable rent levels than those on other low-income tracts. Understanding how gentrification is related to the increased likelihood of a unit being affordable could also be useful to policymakers. If this is due to differing local conditions (location specific policies, stronger organizing networks or nonprofit institutions, more robust growth in housing supply, etc.), understanding the particular drivers of affordability in this context could be valuable in shaping future policy. Generally speaking, better understanding

what factors are shaping geographic differences could help researchers and policymakers better understand the causal mechanisms leading to more or less costly housing markets.

While there is clear evidence of filtering variation across ethno-racial and socioeconomic groups, further investigation into more localized drivers of this variation would be useful as well. As mentioned previously, the uneven distribution of BIPOC and low-income households across and within cities makes evaluating their outcomes more closely important. While there is evidence of obstacles to attaining NOAH for both BIPOC and low-income households, outcomes for low-income, Black and Hispanic/Latino households are particularly challenging. For example, understanding whether the variation in outcomes persists within more granular geography (e.g., census tract) or outcomes for those households are derived from spatially specific differences (e.g., local poverty level, proximity to transit or other resources) would be an important distinction. Given mixed evidence regarding the biggest drivers of changing affordability and the granularity of those drivers (e.g., city- versus neighborhood-level factors), further investigation of how these differential outcomes manifest would clarify possible causal mechanisms and appropriate policy interventions.

Lastly, identifying LIHTC units ultimately was difficult and unsuccessful within the AHS sample. The AHS-provided geocodes either were not rooftop-accurate or otherwise had too much variation from the Google-generated geocodes of LIHTC addresses to accurately identify LIHTC buildings and units¹⁰². While specific outcomes were not disclosed from the IUF data, the numerous tests, including attempts at a fuzzy matching process, failed to accurately identify and remove LIHTC units from the assessment of NOAH. Thus, a more precise understanding of

¹⁰² Wilson et al. (2024) found Google geocodes to be more accurate in general compared to HUD-provided LIHTC geocodes

the NOAH stock would be possible if future researchers are able to more accurately identify and remove those units from similar analyses of NOAH units and filtering dynamics.

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APPENDIX

Table 53: Racial composition of final occupants, by initial occupant race/ethnicity, all units (top) and renter-end units (bottom), gross rent¹⁰³

All units		Race/Ethnicity (Final Year)				
Race/Ethnicity (Base Year)		All others	Asian	Black	Latino / Hispanic	White, non-Hispanic
	All others	29.50%	0.93%	1.46%	0.68%	0.76%
	Asian	9.31%	59.83%	3.42%	2.95%	2.80%
	Black	12.84%	5.86%	71.01%	7.90%	3.93%
	Latino/Hispanic	11.77%	7.09%	8.72%	68.80%	4.77%
	White, non-Hispanic	36.59%	26.29%	15.39%	19.67%	87.74%
Renter end units		Race/Ethnicity (Final Year)				
Race/Ethnicity (Base Year)		All others	Asian	Black	Latino / Hispanic	White, non-Hispanic
	All others	19.98%	1.24%	2.06%	0.87%	1.60%
	Asian	10.29%	49.41%	5.15%	3.94%	6.14%
	Black	13.14%	8.57%	61.24%	11.33%	9.09%
	Latino/Hispanic	14.46%	10.89%	13.72%	63.36%	10.44%
	White, non-Hispanic	42.14%	29.88%	17.83%	20.51%	72.73%

Table 54: Percentage of units that are affordable, by race/ethnicity shifts, all (top) and renter-end units (bottom), gross rent

All units		Race/Ethnicity (Final Year)				
Race/Ethnicity (Base Year)		All others	Asian	Black	Latino / Hispanic	White, non-Hispanic
	All others	38.85%	36.28%	42.98%	15.84%	21.21%
	Asian	12.61%	36.71%	21.20%	12.33%	17.44%
	Black	31.30%	22.63%	47.09%	24.93%	28.79%
	Latino/Hispanic	23.72%	22.82%	32.29%	40.40%	20.86%
	White, non-Hispanic	25.87%	17.73%	22.48%	21.63%	39.16%
Renter end units		Race/Ethnicity (Final Year)				
Race/Ethnicity (Base Year)		All others	Asian	Black	Latino / Hispanic	White, non-Hispanic
	All others	18.57%	5.98%	44.74%	13.83%	12.60%
	Asian	2.32%	26.47%	17.02%	6.13%	7.91%
	Black	22.14%	12.89%	36.91%	21.51%	19.39%
	Latino/Hispanic	9.14%	20.51%	26.99%	26.77%	13.20%
	White, non-Hispanic	12.37%	8.42%	20.67%	16.22%	18.68%

Table 55: Percentage of units that are affordable, by whether race/ethnicity shifted, renter-end units, gross rent

	% Affordable	95% CI
No change in race/ethnicity	25.34%	(23.80%, 26.87%)
Change in race/ethnicity	16.69%	(14.89%, 18.48%)

¹⁰³ Based on a more limited sample derived from the Public Use File (PUF) – true for all tables on this page

Table 56: Ratio of share of units sourced from an ethno-racial group to the source group's population share, renter-end units, gross rent

Race/Ethnicity (Base Year)	Race/Ethnicity (Final Year)					Pop. Share
	All others	Asian	Black	Latino / Hispanic	White, non-Hispanic	
All others	9.09	0.57	0.94	0.40	0.73	2.20%
Asian	1.05	5.02	0.52	0.40	0.62	9.84%
Black	0.59	0.39	2.77	0.51	0.41	22.12%
Latino/Hispanic	0.52	0.39	0.49	2.28	0.38	27.75%
White, non-Hispanic	1.11	0.78	0.47	0.54	1.91	38.10%