Is Filtering a Reliable Source of Low-Cost Housing Supply?

Heterogenous Outcomes in the American Housing Survey, 1985-2021

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Abstract

Filtering of housing units—the process through which housing units over time serve occupants with lower or higher incomes—is a primary source of low-cost housing supply in the United States. Because new construction of market-rate housing units is often not possible at price points affordable to low-income households, the supply of low-cost units in the private market depends on downward filtering of housing units from higher price levels. However, the extent of filtering can vary widely in response to local housing market conditions, and this variation carries implications for the affordable housing strategies used in different areas.

This paper uses the American Housing Survey (AHS) panels for 1985-2013 and 2015-2021 to construct a repeat income measure of filtering. The analyses then describe the presence and extent of variation in filtering outcomes across time periods, price points, and metropolitan areas. The results show significant variation across all three domains. Temporal analyses document significant changes in the extent of filtering across multiple time periods. In particular, the estimates for 2015-2021 suggest that downward filtering of housing units stalled or reversed in many areas as housing markets tightened. The extent of downward filtering is also shown to be significantly weaker in high-appreciation metropolitan areas like San Francisco and Los Angeles compared to lower-appreciation areas. These findings highlight the importance of heterogeneity in filtering outcomes to the conclusions drawn for policy. They also provide insight into the potential limitations of filtering as a source of affordable housing supply.

Introduction

Filtering of housing units— the process through which housing units over time serve occupants with lower or higher incomes —is a primary source of low-cost housing supply in the United States (Eggers and Moumen 2020). While the Low Income Housing Tax Credit (LIHTC), inclusionary zoning, and other housing assistance programs support the construction of a limited number of new affordable units, new construction of market-rate housing units is often not possible at price points affordable to low-income households (Garcia 2019). Instead, additions to the supply of low-cost units in the private market rely heavily on downward filtering of housing units from higher price levels.

Debates over the role of filtering as a source of low-cost housing supply have proliferated over the past decade as many cities experienced rising housing costs and sought options for preventing the loss of lower-cost units (La Jeunesse et al. 2019). For example, the high-profile debate in 2015 over San Francisco's Proposition I, which proposed an 18-month moratorium on new development in the Mission District, included heated discussion about whether construction of new high-end residential housing would accelerate or ease rent growth both within the Mission District and throughout the broader metropolitan area.[1] In other areas, proposals related to accessory dwelling units, missing middle housing options, and other zoning and land use reforms frequently seek to encourage the development of new units affordable to middle- and lower-income households (Garcia et al. 2022; Wegman 2020).

At the center of these debates is a set of empirical questions about housing filtering. Do housing units filter downward to lower-income occupants over time? Does filtering reach all

[1] Refer to Hankinson (2018) for survey evidence measuring voter perceptions of the tradeoffs between housing development and affordability in San Francisco following the 2015 election, which included multiple propositions related to housing policy.

segments of the housing market including the lowest-cost housing stock? Has filtering been a consistent source of lower-cost housing units in all time periods? Are there metropolitan areas where filtering speeds have slowed or even reversed direction? As these questions illustrate, understanding the role of filtering as a source of affordable housing supply requires attention to the potential for heterogeneity in filtering outcomes across multiple dimensions.

This paper uses the American Housing Survey (AHS) panels for 1985-2013 and 2015-2021 to construct a repeat income measure of filtering similar to the one proposed by Rosenthal (2014) and adopted by Liu et al. (2022). The findings then build on the empirical evidence in these papers by describing the presence and extent of heterogeneity in filtering outcomes across time periods, price points, and metropolitan areas.

First, temporal analyses show significant variation in filtering outcomes across time. When the AHS data for 1985-2021 is separated into four panels of similar length, the estimates show significant changes in the extent of filtering across each of the four time periods. In particular, the estimates for 2015-2021 show the weakest filtering outcomes of any period, suggesting that filtering may have stalled or even reversed in many areas as housing markets tightened in the late 2010s. Second, the results find significant variation in filtering speeds between higher- and lower-cost segments of the housing market, with greater downward filtering among higher-cost tiers than among lower-cost tiers.

Third, the analyses measure the extent of variation in filtering rates across metropolitan areas, showing that national-level estimates of filtering should not be extrapolated to individual metropolitan areas. Instead, filtering is significantly weaker in a subset of high-appreciation metropolitan areas like San Francisco and Los Angeles compared to lower-appreciation areas like Chicago and Indianapolis. These findings illustrate the importance of heterogeneity in filtering outcomes to the conclusions drawn for policy. They also provide insight into the potential limitations of filtering as a source of affordable housing supply.

Heterogeneity in Filtering Outcomes

While definitions of filtering can vary, the term is commonly used to refer to the expectation that housing units will become more affordable and serve lower-income occupants over time. A more general definition, however, is that filtering is the process through which housing units serve different occupants and uses over time as they age. This latter definition is inclusive of the potential for housing units to filter down to lower-income households over time, as well as the possibility for housing units to filter upwards to higher-income households. It also recognizes the potential for units to move into and out of the residential housing stock as some units shift between residential and commercial or other uses.

The common use of the term filtering to refer to downward filtering reflects the expectation that housing units will deteriorate and become relatively less desirable over time. The potential for aging of the existing stock to produce downward filtering can be illustrated with an example of the chain of moves produced in response to new construction in a static environment where all other factors are held constant (Weicher and Thibodeau 1988). In this environment, a newly constructed unit that is of higher quality than other units in the stock will attract demand, leading a household to move into the new unit and leave its former unit vacant and available to others. Because the departing occupants are no longer competing for the vacated unit, demand is reduced, which makes the vacated unit available at a lower price that might be affordable to a household with a lower income than the departing occupant. This process then repeats itself until a vacated unit does not have any demand and drops out of the housing stock.

Through this process, a new addition to housing supply might be hypothesized to produce downward filtering among other existing units in the housing stock.

While this simplified example offers intuition about the filtering process, it also helps to illustrate how filtering is likely to be more complicated in dynamic housing markets. For example, the filtering process in this simplified example would be halted by any population growth or new household formation—unless such increases in demand were allowed to also trigger a supply response. In actual housing markets, which are continuously adjusting to changes in demand and supply, the extent of filtering is an equilibrium outcome that is affected by the full spectrum of factors that influence supply and demand.

Discussion of both the concept of filtering and the potential for variation in filtering speeds dates back as far as the early 1900s. Ratcliff (1949) formalized these discussions into the classic model of filtering, and a large literature explores alternative models of the filtering process (Arnott and Braid 1997; Ohls 1975; Sweeney 1974).[2] While these studies explore multiple aspects of the filtering process, the potential for heterogeneity in filtering speeds is also present. For example, attention is given to whether new construction of higher-quality housing generates filtering that affects the price or supply of the lowest-quality stock (Galster 1996; Schall 1981). Other studies examine the interaction of filtering processes across submarkets and neighborhoods, including discussion of filtering's role in tipping processes associated with neighborhood change (Galster and Rothenberg 1991; Coulson and Bond 1990).

The empirical evidence on filtering generally corroborates the hypothesis that housing units filter down on average, but also recognizes the presence of heterogeneity in filtering

[2] Refer to Baer and Williamson (1988) for a more extensive review of the early filtering literature.

speeds. Weicher and Thibodeau (1988) examine the relationship between new construction and the supply of lower quality housing, concluding that their findings are consistent with the presence of downward filtering.[3] More recently, Weicher et al. (2017) use the 1985-2013 panel of the American Housing Survey to describe the sources of the low-cost rental stock.[4] Among units affordable to households making less than 50 percent of the area median income, 23 percent of units nationally in 2013 had filtered down from higher rent levels since 1985. However, across the seven metropolitan areas with sufficient samples to produce separate estimates, this share ranged from 22 percent in Detroit to 43 percent in Northern New Jersey.

Rosenthal (2014) proposed the repeat income method as an empirical approach for directly measuring the filtering rate. By following the AHS panel of housing units across survey waves, the repeat income method observes the income of newly arriving occupants following multiple turnovers of the same housing unit. These repeated observations allow the analyses to directly observe whether the units filtered downward over time to lower-income households. Using the AHS data for 1985-2011, Rosenthal finds that housing units filtered downward on average during this period. At the same time, he hypothesizes that filtering speeds are likely to vary across geographies, with faster downward filtering in areas with less home price appreciation and slower downward filtering in areas with high home price appreciation. Simulation results show differences in the speed of downward filtering across the nine Census

[3] Refer also to Somerville and Holmes (2001), who empirically examine filtering at the housing unit level, identifying determinants of whether a unit is likely to filter downward or upward over time. While several housing unit attributes are predictive of filtering, the authors conclude that neighborhood conditions have a stronger influence on filtering outcomes.

[4] This method is similar to the approach taken in the Rental Market Dynamics report series produced by the U.S. Department of Housing and Urban Development. Refer to, for example, Eggers and Moumen (2020).

regions and between renter- versus owner-occupied units. However, each of the Census regions and tenure groups shows downward filtering on average during this time period.

Liu et al. (2022) apply the repeat income approach to repeat sales data of owner-occupied properties with mortgages funded by Freddie Mac from 1993-2018, focusing on the potential for temporal and geographic heterogeneity in filtering rates. Their analyses produce evidence that heterogeneity in filtering speeds exists both across metropolitan statistical areas (MSAs) and across neighborhoods within the same MSA. Additionally, they produce estimates from a structural model to estimate how filtering rates varied across time periods. Following significant downward filtering for three early periods, they find that filtering slowed to a precisely estimated zero for 2012-2018.

This study contributes to the empirical literature on heterogeneity in filtering speeds in two ways. First, it examines heterogeneity in filtering outcomes using a large national survey that contains both rental and homeowner units. The resulting estimates complement the evidence in Liu et al. (2022) that documents the presence of temporal and geographic variation in filtering outcomes among repeat sales of owner-occupied units. Second, the analyses extend the set of AHS survey waves in Rosenthal (2014) to include the 2015-2021 panel. The analyses also separate the 1985-2013 panel into three subperiods to examine temporal variation within the 1985-2013 panel. The resulting estimates describe the presence and extent of heterogeneity in filtering outcomes across time periods, price points, and geographies.

This heterogeneity in filtering speeds has important implications for the strategies used to respond to housing affordability challenges. One focus of the early filtering literature was on the impact of new construction of subsidized housing on the incidence of substandard housing and on vacancy and abandonment of market-rate units (Weicher and Thibodeau 1988; Ohls 1975).

More recent studies have asked related questions about the potential for LIHTC and other subsidized housing programs to crowd out other units available to low-income households (Sinai and Waldfogel 2005; Malpezzi 2002). The presence of heterogeneity in filtering rates might help to explain the differences in crowd out rates found in areas with different levels of excess demand for subsidized units. More generally, to the extent that filtering rates stall or reverse among low-cost units or in expensive metropolitan areas, such heterogeneity carries implications for the relative efficiency of subsidizing new construction versus providing tenant-based vouchers.

The presence of heterogeneity in filtering outcomes also carries implications for broader conversations about the strategies used in areas facing severe affordability challenges. Should these areas prioritize strategies like accessory dwelling units, missing-middle housing options, and other approaches that seek to add new units at price points affordable to middle- and lower-income households? Or should they seek only to maximize the total number of units that can be added to the overall housing stock?[5] Understanding the variation in filtering rates across different types of metropolitan areas is central to informing policymakers' responses.

Data and Sample

The primary source of data comes from the American Housing Survey's (AHS) panels for 1985-2013 and 2015-2021. Collected every two years, the AHS contains detailed household and housing unit characteristics for a nationally representative sample of the 50 states and the District of Columbia. The longitudinal design of the AHS follows the same housing units across

[5] While these alternatives are not always mutually exclusive, this question appears frequently in local debates over housing development priorities. For example, Schuetz, Meltzer, and Been (2011) study whether inclusionary zoning programs reduce the total stock of housing units by increasing the cost of construction.

multiple waves, allowing data users to identify turnover and to observe changes in the characteristics of a unit's occupants over time. The analysis period for this study includes an initial panel of housing units that was drawn in 1985 and followed through 2013. A subsequent panel was drawn in 2015 and followed through the end of the analysis period in 2021.[6]

The AHS files are supplemented with several data sources that provide geographic information and that are used to classify metropolitan areas into similar groups for analysis. First, geographic information about the location of sample housing units is added from the internal versions of the AHS. Second, the Federal Housing Finance Agency's (FHFA) all transactions home price index for core-based statistical areas (CBSAs) is used to define home price appreciation at the CBSA level for 1985-2021 following Bogin et al. (2019). Third, county-level data on housing unit growth is collected from the decennial censuses for 1980, 1990, 2000, 2010, and 2020. Lastly, the latitude and longitude location of the center of large metropolitan areas comes from the central business district coordinates dataset created by Fee and Hartley (2013).

While the AHS is designed as a longitudinal panel, the addition and removal of supplemental samples in various years add complexity to longitudinal comparisons. This study therefore defines a base sample that isolates the set of housing units that were either included in the original samples of housing units selected in 1985 and 2015 or added to the sample in subsequent years through the routine additions designed to account for new construction. It excludes units that were added to the AHS sample through special supplements or that were removed through a sample reduction.

[6] An important limitation of using longitudinal panels of this length is that analyses are not able to account for all changes over time in survey data collection, editing, imputation, and other processing steps. For more information about historical changes in the AHS panels, refer to the AHS Historical Changes document [https://www.census.gov/programs-surveys/ahs/tech-documentation/def-errors-changes.html].

The estimates in this paper apply the AHS base weights to produce estimates that are representative of the population of housing units eligible for inclusion in the AHS during this period. The base weights account for differences in the probability of sample selection across units, but do not yet include the nonresponse weighting adjustment or the ratio adjustment factors.[7] The use of the base weights rather than the AHS final weights is driven by two considerations. First, replicate weights are available for the AHS base weights for the full analysis period back to 1985, whereas replicate weights only exist for the final weights beginning in the 2000s. The use of replicate weights is necessary to ensure that estimated variances account for the survey design. Second, the analytical design relies on preserving as much sample as possible to support estimates of heterogeneity in filtering rates. The analyses therefore use the AHS base weights and associated replicate weights to produce all estimates reported in this paper.[8]

Filtering Measures

To measure filtering, this paper uses an empirical approach similar to the repeat income method proposed by Rosenthal (2014). This method is inspired by the repeat sales methodology for measuring changes in home prices, which uses repeated transactions to difference away time-invariant characteristics. Applied to filtering, the repeat income approach uses repeated turnovers to compare changes in the incomes of new occupants over time as housing units age. Similar to repeat sales methods, a strength of this approach is its internal validity in identifying units that

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[7] For more information about AHS weights, refer to the AHS's source and accuracy document: U.S. Census Bureau. "2021 AHS Integrated National Sample: Sample Design, Weighting, and Error Estimation." August 2022. [https://www.census.gov/programs-surveys/ahs/tech-documentation/def-errors-changes.html].

[8] The estimated filtering rates are not highly sensitive to this choice. Refer to the Reviewer Appendix for estimates using the final weights.

filter upward or downward from one occupant to the next. By observing the household income of newly arriving occupants following separate turnovers of the same unit, this approach eliminates concerns about unobserved differences across housing units and about differences between the characteristics of newly-arrived vs. long-tenured occupants. It thereby offers strong internal validity for making inferences about whether individual units with multiple observed turnovers filter upwards or downwards over time.

The tradeoff is that filtering can only be observed for units with at least two turnovers, so estimates based on the repeat income method are not formally representative of the broader population of housing units.[9] Instead, the filtering estimates in this paper provide representative information about the filtering outcomes of housing units that turn over two or more times during the period of each panel and that meet the additional sample inclusion requirements. This limitation is the most restrictive for attempts to extrapolate from the sample estimates to draw conclusions about whether the broader population of housing units filtered upward or downward. It is less restrictive for examining heterogeneity in filtering speeds, which involves the weaker assumption that inclusion in the sample is not correlated with the *differences* in filtering speeds across subgroups.

Applying the repeat income method to the AHS panels for 1985-2013 and 2015-2021 relies on the longitudinal structure of the AHS. Units are defined to have turned over to new occupants if all of the current occupants are different than the previous occupants and no current occupant reports a move-in date prior to the year of the last occupied interview. This definition errs on the side of ensuring that identified turnovers are valid turnovers, so it may slightly

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[9] This issue is similar to the potential for selection bias in repeat-sales home price indices (Gatzlaff and Haurin 1997).

underestimate the total number of turnovers.[10] These turnovers are then used to identify turnover pairs to use as the basis for the repeat income measures of filtering.

Before forming turnover pairs, the analysis first divides the initial AHS panel into three roughly decade-long panels from 1985-1993, 1995-2003, and 2005-2013. These panels allow the 2015-2021 panel to be compared to prior periods of similar length, creating four periods for the temporal comparisons. Turnover pairs are then identified within each of these panels by identifying the first and last turnover for housing units with at least two turnovers.[11] Because filtering rates cannot be validly calculated for zero or negative values of income, turnovers in which the newly arriving occupant reports zero or negative income are excluded from turnover pairs. For these units, the identification of turnover pairs skips over these turnovers and searches for whether an additional turnover exists to form a first-last pair. A similar approach is taken for turnovers with missing information about housing costs, excluding these turnovers and searching for the next available turnover to form a first-last pair.

Two measures of filtering are then defined by comparing the real household income of the arriving-occupant households following the first and last turnover in each turnover pair. First, the mean change in log household income provides an initial measure of the change in household

[10] This definition relies initially on the *samehh* (1985-2013) and *samehhld* (2015-2021) variables, which identify units in which some or all household members changed since the prior occupied interview. Additionally, it uses the move-in year variables to require that no household member reports moving in prior to the year of the last occupied interview. This definition excludes units in which some household members turn over in multiple years such that all household members are eventually different. It may also slightly underestimate the number of turnovers to the extent that responses or imputations produce measurement error in the move-in date variable and households are excluded based on the earliest move-in date.

[11] This approach allows the turnover pair to reflect a slightly longer duration for units that turn over frequently. It also mitigates the potential for selection bias due to the inclusion of multiple turnover pairs from such units.

income between the first and last turnover.[12] While this measure provides a continuous variable that incorporates information about the magnitude of any increase or decrease in household income, it may be sensitive to the presence of outlier values with very large changes in household incomes. A second approach is to estimate the share of units in which income decreased between the first and last turnovers in the pair. This measure provides a more direct estimate of the share of units that filtered downward, but it captures only whether units filtered downward versus upward and not the magnitude of the changes. The analyses frequently report estimates for both measures in order to demonstrate the robustness of the reported findings.

These two measures of income filtering are the primary focus of the filtering analyses in this paper. However, several analyses also report estimates from similar measures that describe changes in real housing costs and the presence of housing cost burdens. These measures provide supplemental context about the extent to which any filtering was accompanied by changes in the monthly costs associated with the units. The mean log change in real monthly housing costs and the percentage of units with a decrease in housing costs are calculated similarly to the comparable measures for income. The cost burden measures include the mean change in the housing cost burden ratio of newly arrived households and the percentage of turnover pairs in which the cost burden decreased.[13] All measures of income, housing costs, and other dollar values are inflation-adjusted to 2021 dollars using the Consumer Price Index Retroactive Series (R-CPI-U-RS).

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[12] The ratio of household income for the last turnover to the first turnover measures the percent change in household income between turnovers. Because the distribution of these ratios is right-skewed, this measure uses the natural log of this ratio to reduce the impacts of the right skew on the mean values.

[13] Changes in the cost burden ratio are topcoded at 100 percent to reduce the influence of outlier values.

Results

The samples of turnover pairs for 1985-1993, 1995-2003, 2005-2013, and 2015-2021 collectively include 50,500 turnover pairs. Table 1 presents descriptive statistics and initial filtering estimates for the pooled sample of turnover pairs from all four decades. Approximately 50 percent of units in this sample were in multifamily buildings, 36 percent were single-family detached units, 9 percent were single-family attached units, and 5 percent were mobile homes. This distribution reflects the higher frequency of turnovers among rental units, which is also reflected in the sample sizes and housing unit characteristics reported for the remaining columns presenting estimates by type of tenure transition. For example, the share of single-family detached units is 20 percent among rent-to-rent transitions, compared to 61 percent among own-to-rent transitions, 66 percent among rent-to-own transitions, and 79 percent among own-to-own transitions. Units in the pooled sample of turnover pairs have on average 2.2 bedrooms and 1.5 bathrooms. The turnovers forming each pair occurred on average 4.7 years apart, and the average age of the unit at the time of the second turnover is 37 years.

The initial filtering estimates in Table 1 suggest that housing units with two or more turnovers filtered downward on average to households with lower incomes, but also that filtering varied significantly by type of tenure transition. First, the mean change in log income estimate is -.018, implying downward filtering on average to households with lower incomes.[14] For this measure, negative values imply downward filtering to occupants with lower incomes and positive values imply upward filtering to occupants with higher incomes, with the size of the estimate showing the magnitude of the increase or decrease. Second, the percentage of turnover

[14] Because this variable is logged, the percent change in income must be calculated by applying the exponential function to this value and subtracting 1. In this case, the estimate of -.018 corresponds with a change of e(-.018) – 1 = -.018, which is a decrease of 1.8 percent.

pairs with an income decrease is 51.2 percent, implying that more than half of the observed turnover pairs filtered downward in the pooled sample. For this measure, higher values indicate more downward filtering to households with lower incomes (in contrast to the mean change in log income measure, for which higher values indicate upward filtering to households with higher incomes). For simplicity of discussion, this section uses downward filtering to imply filtering to households with lower incomes and upward filtering to imply filtering to households with higher incomes—with downward filtering as the default when the discussion references stronger filtering or faster filtering speeds if the direction of filtering is not specified.

The additional columns in Table 1 show sizable differences in the income filtering estimates by tenure transition. While the mean change in log household income of rent-to-rent turnovers is-.036, the estimate is -.262 for own-to-rent transitions, .271 for rent-to-own transitions, and not significantly different from zero for own-to-own transitions. These estimates illustrate the potential influence of tenure transitions on the overall filtering of the housing stock, with own-to-rent transitions contributing on average to downward filtering and rent-to-own transitions contributing on average to upward filtering. The filtering measure reporting the percentage of units with an income decrease shows that this finding is robust to the choice of measure. The estimated shares of units with an income decrease for rent-to-rent and own-to-rent transitions are significantly higher than 50 percent, suggesting that these transitions contribute on average to downward filtering. Conversely, rent-to-own transitions contribute on average toward upward filtering, and the estimate for own-to-own transitions is not significantly different than 50 percent.

An additional finding from the initial filtering measures in Table 1 is that downward filtering of the housing stock to households with lower incomes is not necessarily accompanied by decreases in the cost of housing. For example, both measures of income filtering show significant downward filtering on average among rent-to-rent transitions. However, the mean log change in housing costs for rent-to-rent transitions is not significantly different from zero, and the percentage of rent-to-rent transitions with a housing cost decrease is not significantly different from 50 percent. The result is that the average housing cost burden increased by 1.0 percentage point following rent-to-rent turnovers—despite significant downward filtering to households with lower incomes. The finding illustrates that the presence of downward filtering to households with lower incomes does not necessarily imply any decrease in housing costs.

[INSERT TABLE 1]

Table 2 presents similar estimates separately for each decade panel, documenting the extent of temporal variation in the filtering measures. The initial column repeats the estimates from Table 1, showing that the mean log change in real household income for turnover pairs in the pooled sample is -.018, and the percentage of units with an income decrease is 51.2 percent. The standard errors for these estimates show that they are significantly different than zero and 50 percent, respectively, implying that the sample units filtered downward on average. This result is consistent with the estimates in Rosenthal (2014), which show downward filtering on average for a pooled sample of turnover pairs from 1985-2011. However, the remaining columns of Table 2 show that this finding is sensitive to the period selected.

[INSERT TABLE 2]

While the mean log change in real household income for the pooled sample is -.018, it is negative and significant in only two of the four decades—- .050 percent in 1985-1993 and - .084 in 2005-2013. In contrast, the mean log change in real household income is .022 percent in 1995-2003 and .051 in 2015-2021. These findings are again robust to the choice of measure, with the exception that the estimated percentage of units with an income decrease is not statistically different from 50 percent in 1995-2003. For both measures, the estimated filtering speed in each decade panel is significantly different than the estimate in the prior decade panel. These estimates suggest that the average for the pooled sample conceals significant heterogeneity in filtering speeds across periods.

One possible explanation for this finding might be that changes in the number of tenure transitions across decades contributes to the differences in the filtering rates. For example, the tenure transition rates in Table 2 show that the share of own-to-rent transitions increased from roughly 5-6 percent of turnover pairs in 1985-1993 and 1995-2003 to 9 percent in 2005-2013 before falling to 4 percent in 2015-2021. However, this hypothesis is not borne out by the regressions in Table 3, which use OLS to estimate the differences between decades while controlling for tenure transitions and other housing unit characteristics. The difference between the mean change in log income in 2005-2013 and 2015-2021 without any controls is -.135, compared to -.125 after controlling for differences in the distributions of tenure transitions and housing unit characteristics across decades—a change that is not statistically significant. This result suggests that the changes in filtering outcomes across decades are instead driven primarily by differences in filtering outcomes among units making the same types of tenure transitions.

[INSERT TABLE 3]

The second panel in Table 2 shows the filtering estimates for the sample of turnover pairs making rent-to-rent transitions—i.e., units that were renter-occupied following both turnovers. The estimates again show significant variation in filtering speeds across decades. The mean change in log income among rent-to-rent transitions is - .068 in the 1985-1993 panel, not statistically different from zero in the 1995-2003 panel, -.101 in the 2005-2013 panel, and .029 in the 2015-2021 panel. Each decade panel is significantly different than the estimate for the prior decade panel for both measures of filtering. These results corroborate the conclusion that filtering speeds vary significantly across periods.

The estimates for 2015-2021 additionally suggest that filtering rates slowed significantly in recent years. Both measures of income filtering show upward filtering on average in 2015-2021, and the same is true when the sample is limited to rent-to-rent transitions. These findings supplement the evidence in Liu et al. (2022) that filtering slowed from significant downward filtering prior to 2012 to a precisely estimated zero for 2012-2018 among the own-to-own turnover pairs in their sample. Together, these findings suggest that the filtering process may have stalled or reversed during the last decade. At the same time, the housing cost measures in Table 2 show significant increases in monthly housing costs for 2015-2021, and significantly fewer than 50 percent of households saw a cost burden decrease for 2015-2021. These estimates indicate that the presence of upward filtering during this period was accompanied by decreases in affordability to the new occupants—despite the new occupants' higher incomes.

A second research question is whether the national-level estimates apply evenly to all areas of the country—or whether there is significant variation in filtering rates across metropolitan areas. To examine variation in filtering rates across metropolitan areas, I use geographic information from the internal AHS data to identify the core-based statistical area (CBSA) for each housing unit in the sample, applying 2010 CBSA boundaries consistently to all panels. The sample sizes for individual metropolitan areas are unfortunately too small to precisely estimate filtering rates specific to individual CBSAs. The analyses therefore group CBSAs with similar characteristics to produce estimates for different types of metropolitan areas.

Figure 1 displays a scatterplot of the 50 CBSAs with the largest numbers of housing units in 2020. The y-axis plots each CBSA's total appreciation in home prices from 1985-2021 using the FHFA's all transactions home price index for CBSAs (Bogin et al. 2019). The x-axis plots the total percent growth in housing units from 1980 to 2020 based on the decennial Censuses.[15] This dichotomy provides the basis for grouping large CBSAs into five categories with similar levels of home price appreciation and housing unit growth. The "high appreciation West" CBSAs include Los Angeles, Portland (OR), San Diego, San Francisco, San Jose, and Seattle. The "high appreciation Northeast" CBSAs include Baltimore, Boston, New York City, Philadelphia, and Providence. The "appreciation and growth" CBSAs include Denver, Miami, Nashville, Riverside, Sacramento, Tampa, and Washington DC. The "high growth" metros include Atlanta, Austin, Charlotte, Dallas, Houston, Jacksonville, Las Vegas, Orlando, Phoenix, Raleigh, and San Antonio. The remaining large CBSAs are grouped into a "base category" category that includes CBSAs with lower rates of appreciation and housing unit growth, which is used as the base category for comparing the filtering rates of the other groups. For smaller CBSAs, the home price appreciation rate and housing unit growth rate that bound the "base category" are used to create four categories that group small CBSAs into quadrants with lower versus higher home price appreciation and housing unit growth. The analyses group all non-CBSA counties into one "nonmetropolitan" category due to sample size limitations, and units with missing geographic information or missing data on CBSA home price appreciation are excluded from the analysis sample.[16]

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[15] The housing unit counts for the decennial censuses are drawn from Social Explorer's county-level data, which use reallocation fractions from the longitudinal tract database to account for any changes in county boundaries across decades. The county-level counts are then aggregated into CBSAs using the 2010 boundaries consistently for all decades.
[16] This restriction removes approximately 7 percent of the sample.

[INSERT FIGURE 1]

Table 4 presents estimates of both filtering measures for each of these CBSA groupings. The top panel displays the estimated percentage of units with an income decrease, and the bottom panel presents similar information for the measures of mean log change in real household income. Similar to Table 3, the asterisks in Table 4 reflect whether an estimate is significantly different than the previous period, providing insight into the presence of heterogeneity in filtering speeds across periods. Table 5 partitions the sample into large and small CBSAs and presents OLS regressions that measure the difference between the filtering estimate for each CBSA category and the estimate for the omitted base category, providing insight into the presence of heterogeneity in filtering speeds across geographies.

[INSERT TABLE 4]

[INSERT TABLE 5]

These estimates reveal differences in both filtering speeds and the volatility of filtering speeds across CBSAs. First, the estimates in Table 4 containing the pooled sample for 1985-2021 show that the finding that units filter downward, on average, does not hold for all geographies. Among large CBSAs, the estimates indicate that more than half of units filtered downward only among the base category, the high growth category, and the appreciation and growth category. In contrast, the estimate for the high appreciation West category is not statistically different from 50 percent, and Table 5 shows that the filtering estimate for this group is significantly lower than the estimate for the base category. These findings are consistent with Rosenthal's (2014) hypothesis that geographic variation in filtering speeds might be inversely associated with home price appreciation—i.e., less downward filtering in geographies with higher home price appreciation. This suggests that national-level estimates of filtering conceal significant variation in filtering speeds and should not be extrapolated to individual metropolitan areas.

The presence of slower filtering speeds in the high appreciation West CBSAs is most apparent in 1995-2003 and 2015-2021. The estimates in Table 4 show that the percentage of units with an income decrease fell below 50 percent in the high appreciation West CBSAs during the 1995-2003 and 2015-2021 panels—indicating that sample housing units filtered upward on average to higher income households during these periods. The regression results in Table 5 reinforce that these filtering rates are significantly lower than the base category in the 1995-2003 and 2015-2021 periods.

However, the high appreciation West CBSAs also exhibit significant volatility in their filtering speeds across periods. The asterisks in Table 4 indicate whether the filtering estimate is significantly different from the estimate for the prior period, showing that the filtering speeds in the base category CBSAs did not change significantly across periods. In contrast, the filtering estimates in the high appreciation West CBSAs changed significantly across each of the four decade panels. The high appreciation West CBSAs show significant downward filtering on average in 1985-1993, upward filtering in 1995-2003, downward filtering in 2005-2013, and upward filtering in 2015-2021. In fact, Table 5 indicates that the percentage of units with an income decrease was significantly higher in the high appreciation West CBSAs than the base category in 2005-2013, implying significantly faster downward filtering during the foreclosure crisis period (with the caveat that this finding is not replicated for the measure of change in log income). Together, the estimates in Tables 4 and 5 show significant heterogeneity across large metropolitan areas in both average filtering speeds and the volatility of filtering speeds across periods.

The small CBSA estimates show little significant variation in filtering speeds across the CBSA categories. The low appreciation/low growth category is the only group to show significant downward filtering on average in the pooled estimates for 1985-2013. While the estimates for the two high appreciation categories are very close to 50 percent, they are not significantly different from the base category. Similarly, the estimates in Table 5 comparing the relative filtering speeds of the high appreciation/low growth category to the base category do not show significant differences in any of the four decades.

Because CBSAs include expansive geographies that extend into exurban areas, Table 6 examines the extent to which the differences in filtering rates across CBSAs differ between the central areas of these CBSAs and more distant exurban geographies. Sample housing units in the 50 largest CBSAs are categorized into three groups that represent increasing distance from the central business district of the CBSA's primary city.[17] All sample housing units in each CBSA are then categorized into groups of roughly similar sample sizes that reflect increasing distance from the central business district. These categories are broad groupings that each include a diversity of neighborhoods, so they do not precisely define central, suburban, and exurban locales. Instead, they are used only to test whether core areas closer to the center of these CBSAs exhibit different filtering speeds than outlying areas.

Table 6 presents estimates that compare filtering speeds across these distance categories. The analyses present simple OLS models that use the innermost ring as the omitted base category and measure the difference in filtering speeds between each outer ring and this base category. The top two panels show results for the pooled sample containing all 50 of the largest

[17] The latitude and longitude associated with the central business district of the primary city in each CBSA come from Fee and Hartley (2013). Refer to Holian (2019) for discussion of the tradeoffs between alternative methods for determining the location of city centers.

CBSAs, and the bottom two panels show results specific to the high appreciation CBSAs. Across panels, the estimates provide little support for the hypothesis that the central areas of CBSAs might exhibit even greater variation in filtering speeds than the CBSA as a whole. For example, the estimates for high appreciation/low growth CBSAs in 1995-2003 and 2015-2021 do not provide any evidence to suggest that upward filtering during these periods in the high appreciation/low growth CBSAs was more pronounced in the central areas than in the exurban areas. Instead, the only significant difference between the inner ring and the outer ring appears for the pooled sample of large CBSAs in 2005-2013; however, it is only significant at the 10 percent level and weakens in the estimates using the measure of log change in household income.[18]

[INSERT TABLE 6]

A final research question is whether filtering speeds vary for higher- versus lower-cost units. Because new construction frequently adds units at higher price points, one might expect filtering speeds to be fastest among higher-cost units and slower at lower price tiers. This hypothesis reflects the finding that filtering speeds are faster in the years immediately following new construction and slower among older homes (Liu et al. 2022; Rosenthal 2014). To the extent that older homes are more common in the lower-cost housing stock, one might expect slower filtering speeds. Additionally, to the extent that new housing supply does not fully meet demand from population growth and other sources, the filtering process might stall before reaching the lowest-cost housing stock.

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[18] Given the broad definition of the CBSA distance categories, it is not clear how to interpret the differences between the inner ring and the middle ring. These rings do not map precisely to any concept of suburban areas, so caution should be applied in interpreting these estimates. Further research using more precise definitions and larger sample sizes is needed to explore variation in filtering rates across neighborhoods within CBSAs.

Table 7 presents regressions that compare filtering speeds across different segments of the housing cost distribution. The housing cost measure for this analysis might ideally be a baseline measure collected prior to the first wave of each panel and collected consistently across decade panels. The analysis approximates such a measure by using the housing cost data collected during the first occupied interview of each decade panel when it is prior to the first turnover. To increase the sample for the analyses, I also include housing cost measures collected during an occupied interview that occurs between the first and second turnover pair when available. The sample sizes for the analyses in Table 7 are therefore reduced due to the exclusion of cases for which no housing cost value is observed that meets these requirements.[19] The housing cost tiers in Table 7 use this measure to separate housing units into quartiles within each CBSA or CBSA group.[20]

[INSERT TABLE 7]

The estimates in Table 7 show significantly slower filtering in the lowest housing cost tier relative to units in the highest cost tier. The estimate of -.024 for the pooled sample implies that the percentage of housing units that filtered downward is 2.4 percentage points lower in the bottom housing cost tier relative to the highest cost tier. The corresponding estimate for each of the decade panels has a negative sign, although only the estimate for 1995-2003 is statistically significant. The estimates for the mean change in log income also show significantly slower

[19] The reduction in sample occurs because the housing cost measure does not use values from the same survey wave as the either turnover in a pair. The rationale is that measurement error in the income and housing cost measures within the same survey wave may be correlated due to the imputation process. Because the AHS does not use longitudinal imputation, using values from other survey waves eliminates this concern.

[20] For large CBSAs, units are rank ordered by housing cost within each CBSA and then separated into quartiles with equal sample sizes. For small CBSAs, this process is repeated using the CBSA categories in Table 4.

filtering in the lowest housing cost quartile for the pooled sample, 1985-1993, and 1995-2003. These estimates are consistent with the hypothesis that filtering speeds are faster among higher-cost units, with slower filtering rates or upward filtering on average among units in the lowest cost tier. However, this effect weakens and is no longer statistically significant in 2005-2013 and 2015-2021. One possible explanation for the weakened differences might be that the effects of the foreclosure crisis and subsequent housing recovery affected the housing stock broadly and reduced the differences between segments. However, other explanations may also exist, so these effects should be investigated in future research with larger samples and other sources of housing cost information.

Discussion

Filtering processes have profound implications for the supply of lower-cost housing units, and more empirical evidence is needed to shed light on the processes through which housing units serve different occupants and uses over time as they age. This paper uses the longitudinal structure of the American Housing Survey to produce survey-based estimates of filtering using a repeat income approach. The analyses focus on measuring the presence and extent of heterogeneity in filtering outcomes across time, geographies, and price tiers, showing significant variation in filtering speeds across all three dimensions.

First, the results produce separate filtering estimates for 1985-1993, 1995-2003, 2005-2013, and 2015-2021, showing variation in filtering speeds across time. While sample housing units filtered downward on average in 1985-1993 and 2005-2013, filtering rates stalled or show significant upward filtering on average in 1995-2003 and 2015-2021. These results add complexity to the findings in Rosenthal (2014) and Liu et al. (2022) that show downward filtering on average across longer periods. Instead, this temporal variation in filtering speeds suggests that filtering is likely not constant across time, but rather is an equilibrium outcome that reflects changes in housing market conditions. As a result, further research should examine the relationship between filtering speeds and the housing market booms and busts that have characterized recent decades. In particular, the estimates for 2015-2021 exhibit the weakest filtering outcomes of the four periods, raising concerns that the downward filtering of units to lower-income households may have stalled or reversed in recent years. This result is consistent with concerns that underbuilding and declining vacancy rates produced extremely tight housing markets in many areas.

Second, the estimates show that national-level estimates of filtering rates should not be extrapolated to individual metropolitan areas. Instead, significant variation in filtering rates exists between high appreciation areas like San Francisco and Seattle and a base category of CBSAs with lower appreciation and housing unit growth that includes areas like Chicago and Kansas City. The high appreciation areas show significantly slower filtering rates on average for the pooled sample containing the full period from 1985-2021, as well as for the 1995-2003 and 2015-2021 periods. Additionally, the high appreciation areas show greater volatility in filtering speeds across periods. Where the estimated filtering speeds for the base category CBSAs do no change significantly across periods, the estimated filtering speeds for the high appreciation CBSAs significantly accelerated and decelerated across periods. These findings underscore the need for more empirical evidence that both describes and explains variation in filtering speeds across geographies, as well as across boom and bust periods of the housing market.[21]

[21] Additionally, future studies should identify opportunities to examine within-CBSA variation in filtering speeds across neighborhoods using approaches similar to Liu et al. (2022). While sample size limitations prevent such analyses in this paper, such work is needed to shed light on the potential for heterogeneity in filtering speeds at smaller geographic scales—and to close the gap between the filtering literature and the literatures on neighborhood gentrification,

Lastly, the results also show significant variation in filtering speeds between higher- and lower-cost segments of the housing market. This result is consistent with the hypothesis that filtering may be most effective at increasing the supply of middle- and higher-cost units and less effective at increasing the supply of lower-cost units. However, the differences across price tiers are significant only in 1985-1993 and 1995-2003, diminishing in 2005-2013 and 2015-2021. These mixed results suggest that more research is needed to better understand variation in filtering speeds across price segments of the housing market.

In the interim, the presence of significant variation in filtering rates across time periods and metropolitan areas suggests that the optimal strategies for responding to affordable housing challenges are also likely to vary. While robust downward filtering of housing units may produce sufficient low-cost housing stock in some periods and geographies, filtering of market-rate units may not be a reliable source of affordable housing supply during housing market booms or in geographies experiencing strong home price appreciation. In these areas, supplying affordable housing units may require greater reliance on production of new housing units through LIHTC, inclusionary zoning, and other strategies for producing new affordable units (as a supplement to efforts to ease supply constraints and encourage increases in the total housing stock). Slower filtering rates in these areas might also provide a rationale for efforts to encourage construction of market-rate units at price points affordable to middle- and lower-income households; however, further research on the filtering outcomes of such units is needed to determine whether such units have larger impacts on the low-cost housing stock than filtering that results from the construction of new high-cost units.

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displacement, and the within-CBSA migration of higher- and lower-income households (Couture and Handbury 2017; Ding et al. 2016; Kneebone and Berube 2013).

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Reviewer Appendix: Sensitivity Analyses for Use of the Base Weights Versus Final Weights

The estimates presented and discussed in this paper apply the AHS base weights to produce estimates that are representative of the population of housing units eligible for inclusion in the AHS during this period. The use of the base weights rather than the AHS final weights is driven by two considerations. First, replicate weights are available for the AHS base weights for the full analysis period back to 1985, whereas replicate weights only exist for the final weights beginning in the 2000s. The use of replicate weights is necessary to ensure that estimated variances account for the survey design. Second, the analysis design relies on preserving as much sample as possible to support estimates of heterogeneity in filtering rates.

The filtering estimates in these tables are not highly sensitive to the use of the base weights instead of the final weights. To demonstrate the robustness of the paper's findings, this appendix presents results that use the final weights to replicate the tables that describe heterogeneity in filtering rates across time, geographies, and price points. Specifically, the appendix tables replicate the results in Tables 2, 5, and 7.

[TABLE A-1]

[TABLE A-2]

[TABLE A-3]

Tables and Figures

Table 1: Descriptive Statistics for the Pooled Sample and by Type of Tenure Transition.

	Pooled 1985-2021		Rent-to-Rent		Own-to-Rent		Rent-to-Own		Own-to-Own	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Income Filtering										
Percent with income decrease	51.2%	0.28%	51.8%	0.31%	61.2%	1.01%	40.4%	0.84%	50.2%	0.66%
Mean change in log income	-0.018	0.006	-0.036	0.008	-0.262	0.025	0.271	0.017	0.004	0.013
Housing Costs										
Percent with housing cost decrease	50.4%	0.26%	50.2%	0.30%	55.5%	0.95%	47.2%	0.83%	50.7%	0.55%
Mean change in log housing costs	0.012	0.005	0.004	0.007	-0.127	0.028	0.184	0.022	0.013	0.009
Housing Cost-to-Income Ratio										
Percent with cost ratio decrease	48.5%	0.29%	47.6%	0.31%	43.0%	1.12%	56.2%	0.79%	50.2%	0.62%
Mean change in housing cost ratio	0.005	0.002	0.010	0.002	0.053	0.007	-0.057	0.005	-0.002	0.003
Housing Unit Characteristics										
% single-family detached	36.3%	0.30%	19.9%	0.29%	61.1%	1.06%	66.0%	0.92%	78.6%	0.64%
% single-family attached	8.7%	0.16%	8.9%	0.19%	10.4%	0.66%	8.9%	0.47%	7.1%	0.29%
% multifamily	50.4%	0.33%	68.6%	0.34%	16.7%	0.70%	18.0%	0.72%	5.5%	0.30%
% mobile home	4.6%	0.22%	2.5%	0.17%	11.8%	1.04%	7.1%	0.56%	8.8%	0.58%
Mean # bedrooms	2.2	0.01	1.9	0.01	2.7	0.02	2.7	0.02	3.1	0.01
Mean # bathrooms	1.5	0.01	1.3	0.01	1.7	0.02	1.7	0.02	2.1	0.01
Mean age of unit at turnover	37.1	0.20	39.2	0.22	35.2	0.55	37.6	0.48	29.3	0.34
Mean years between turnovers	4.7	0.01	4.8	0.01	5.0	0.04	4.4	0.04	4.3	0.02
N	50500		35000		2800		3900		8500	

Notes: The U.S. Census Bureau reviewed this data product for unauthorized disclosure of confidential information and approved the disclosure avoidance practices applied to this release. CBDRB-FY23-POP001-0045.

Table 2: Variation in Filtering Estimates by Time Period.

	Pooled 1985-2021		1985-1993		1995-2003		2005-2013		2015-2021	
	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE
All Transition Types										
Percent with income decrease	51.2%	0.28%	52.4%	0.45%**	49.5%	0.49%***	54.2%	0.66%***	48.0%	0.46%***
Mean change in log income	-0.018	0.006	-0.050	0.009***	0.022	0.011***	-0.084	0.017***	0.051	0.012***
Percent with housing cost decrease	50.4%	0.26%	56.7%	0.46%***	44.6%	0.45%***	55.6%	0.50%***	43.3%	0.53%***
Mean change in log housing costs	0.012	0.005	-0.103	0.014***	0.133	0.010***	-0.041	0.009***	0.066	0.009***
Percent with cost ratio decrease	48.5%	0.29%	49.9%	0.48%***	47.4%	0.47%***	48.0%	0.68%	48.5%	0.50%
Mean change in housing cost ratio	0.005	0.002	-0.005	0.003***	0.013	0.003***	0.010	0.004	0.003	0.003
Rent-to-Rent Transitions Only										
Percent with income decrease	51.8%	0.31%	53.0%	0.53%*	50.3%	0.58%***	54.5%	0.78%***	48.9%	0.56%***
Mean change in log income	-0.036	0.008	-0.068	0.011**	0.008	0.015***	-0.101	0.020***	0.029	0.016***
Percent with housing cost decrease	50.2%	0.30%	56.6%	0.53%***	45.6%	0.59%***	54.1%	0.61%***	43.0%	0.60%***
Mean change in log housing costs	0.004	0.007	-0.139	0.021***	0.135	0.012***	-0.018	0.011***	0.053	0.010***
Percent with cost ratio decrease	47.6%	0.31%	49.0%	0.58%**	47.2%	0.55%**	46.1%	0.73%	48.1%	0.60%**
Mean change in housing cost ratio	0.010	0.002	-0.003	0.004***	0.015	0.004***	0.023	0.005	0.005	0.005**
% of Units by Transition Type										
Rent to rent	68.5%	0.26%	70.4%	0.45%***	65.7%	0.45%***	68.0%	0.54%***	70.2%	0.45%***
Own to rent	6.0%	0.12%	5.7%	0.22%	5.2%	0.24%*	9.0%	0.31%***	3.7%	0.19%***
Rent to own	7.9%	0.12%	8.3%	0.23%	9.0%	0.28%*	6.1%	0.26%***	8.2%	0.25%***
Own to own	17.6%	0.20%	15.6%	0.37%***	20.1%	0.40%***	16.9%	0.42%***	17.9%	0.35%*
N	50500		12000		12000		11000		15500	

Notes: The U.S. Census Bureau reviewed this data product for unauthorized disclosure of confidential information and approved the disclosure avoidance practices applied to this release. CBDRB-FY23-POP001-0045.

***p<.01, **p<.05, *p<.10; asterisks indicate whether measures are statistically different from the estimate for the prior period. Asterisks for 1985-1993 compare to the pooled sample for 1985-2021.

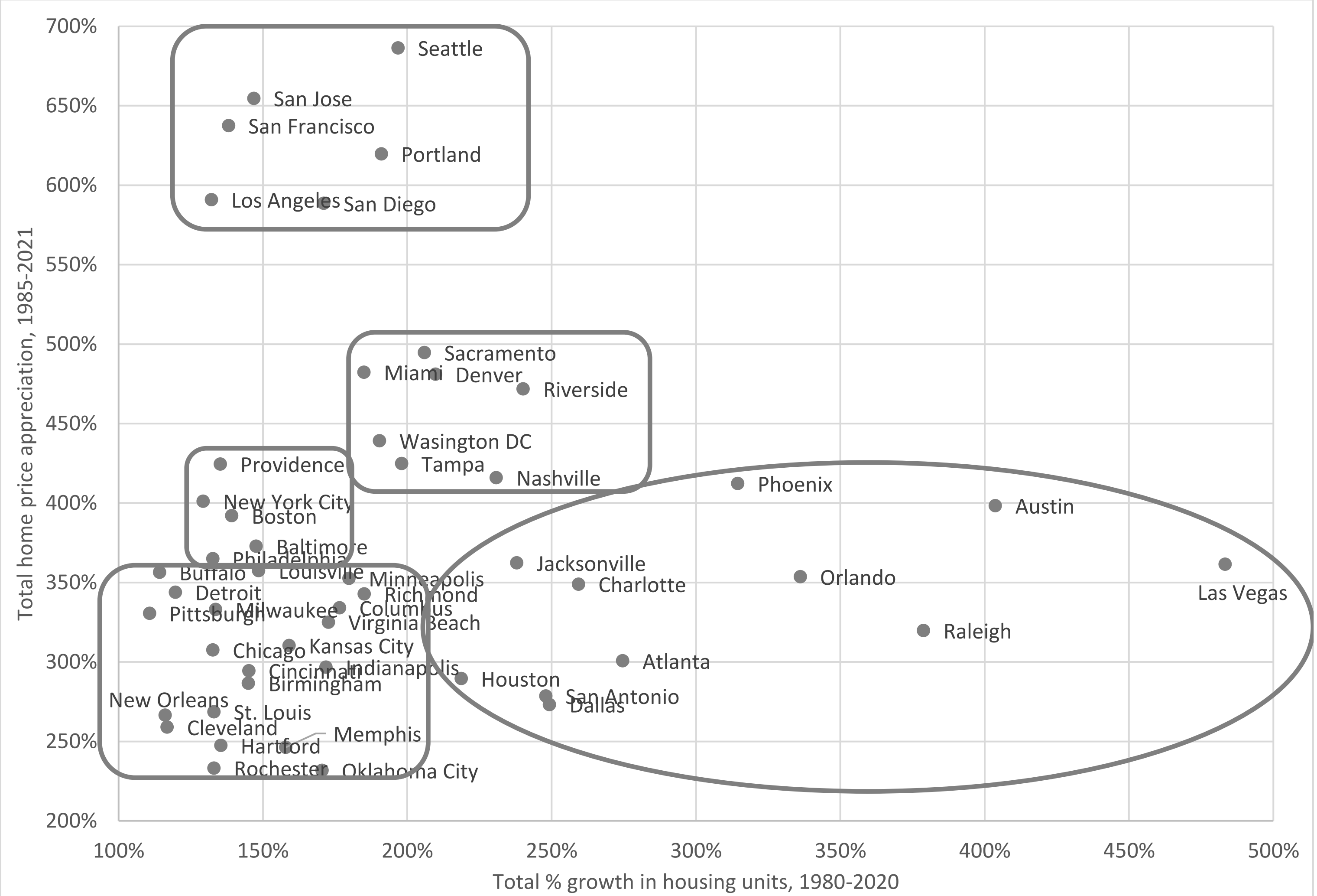
Table 3: OLS-Estimated Differences in Filtering Outcomes by Time Period.

Dependent variable:	% income decrease		% income decrease		Change in log income		Change in log income	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Intercept	0.480	0.005***	0.474	0.013***	0.051	0.012***	0.062	0.035*
1985-1993	0.044	0.007***	0.045	0.007***	-0.102	0.017***	-0.099	0.019***
1995-2003	0.015	0.007**	0.020	0.008**	-0.029	0.017*	-0.036	0.019*
2005-2013	0.062	0.008***	0.060	0.008***	-0.135	0.021***	-0.125	0.022***
2015-2021 (omitted)								
Covariates	No		Yes		No		Yes	
N	50500		50500		50500		50500	

Notes: Covariates include controls for each type of tenure transition, as well as the set of housing unit characteristics listed in Table 1. The U.S. Census Bureau reviewed this data product for unauthorized disclosure of confidential information and approved the disclosure avoidance practices applied to this release. CBDRB-FY23-POP001-0045.

***p<.01, **p<.05, *p<.10

Figure 1: Figure: Scatterplot of CBSAs by Long-Term Home Price Appreciation and Housing Unit Growth.



Notes: Total home price appreciation is the total percent change from 1985 to 2021 in the FHFA all transactions home price index for CBSAs. Total percent growth in housing units is the percent change in total housing units between the 1980 and 2020 decennial censuses, using 2010 CBSA boundaries.

Table 4: Filtering Estimates by CBSA Type.

	Pooled 1985-2021		1985-1993		1995-2003		2005-2013		2015-2021	
	%	SE	%	SE	%	SE	%	SE	%	SE
Percent with income decrease										
Large, Base category	51.9%	0.66%	53.6%	1.28%	51.1%	1.18%	52.6%	1.31%	50.0%	1.11%
Large, High growth	52.6%	0.63%	57.5%	1.49%***	50.6%	1.23%***	54.1%	1.32%**	48.7%	1.00%***
Large, Appreciation and growth	51.9%	0.74%	54.5%	1.68%	48.6%	1.39%***	56.9%	1.65%***	47.1%	1.38%***
Large, High appreciation Northeast	50.5%	0.94%	51.0%	1.49%	46.4%	1.59%**	55.9%	2.29%***	48.8%	1.55%***
Large, High appreciation West	50.0%	0.76%	53.0%	1.46%*	44.6%	1.32%***	56.3%	1.34%***	46.0%	1.34%***
Small, low apprec, low growth	51.0%	0.53%	51.2%	1.10%	51.4%	0.95%	53.1%	1.23%	47.5%	1.16%***
Small, low apprec, high growth	51.7%	1.10%	50.4%	1.95%	52.2%	2.06%	55.0%	1.83%	48.3%	2.12%**
Small, high apprec, high growth	50.0%	1.31%	48.3%	2.12%	51.7%	3.00%	51.5%	2.68%	48.4%	2.23%
Small, high apprec, low growth	50.1%	1.16%	47.9%	1.92%	48.0%	2.16%	55.9%	2.51%**	48.1%	2.36%**
Nonmetropolitan	50.0%	1.62%	50.4%	2.98%	51.1%	2.79%	52.4%	3.36%	45.7%	2.71%
Mean change in log income										
Large, Base category	-0.039	0.016	-0.063	0.026	-0.011	0.030	-0.071	0.040	-0.008	0.032
Large, High growth	-0.052	0.016	-0.152	0.027***	-0.006	0.030***	-0.098	0.044*	0.036	0.025***
Large, Appreciation and growth	-0.025	0.017	-0.108	0.033**	0.057	0.035***	-0.134	0.036***	0.096	0.031***
Large, High appreciation Northeast	-0.008	0.020	-0.008	0.028	0.052	0.041	-0.100	0.049**	0.022	0.049*
Large, High appreciation West	0.001	0.018	-0.071	0.031**	0.124	0.032***	-0.132	0.036***	0.086	0.033***
Small, low apprec, low growth	-0.023	0.014	-0.038	0.022	-0.008	0.029	-0.097	0.030**	0.064	0.037***
Small, low apprec, high growth	-0.028	0.022	-0.007	0.037	-0.018	0.037	-0.063	0.041	-0.014	0.050
Small, high apprec, high growth	0.017	0.036	-0.004	0.054	-0.048	0.074	0.039	0.067	0.068	0.063
Small, high apprec, low growth	0.005	0.022	0.019	0.037	0.042	0.058	-0.116	0.055**	0.101	0.054***
Nonmetropolitan	0.041	0.033	0.001	0.060	0.046	0.048	0.007	0.079	0.114	0.057
N	47000		10000		11000		11000		15100	

Notes: The U.S. Census Bureau reviewed this data product for unauthorized disclosure of confidential information and approved the disclosure avoidance practices applied to this release. CBDRB-FY23-POP001-0045.

***p<.01, **p<.05, *p<.10; asterisks indicate whether measures are statistically different from the estimate for the prior period. Asterisks for 1985-1993 compare to the pooled sample for 1985-2021.

Table 5: OLS-Estimated Differences in Filtering Outcomes by Metropolitan Area Type.

	Pooled 1985-2021		1985-1993		1995-2003		2005-2013		2015-2021	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Large CBSAs - Percent with income decrease										
Intercept	0.519	0.007***	0.536	0.013***	0.511	0.012***	0.526	0.013***	0.500	0.011***
Base category (omitted)										
High growth	0.007	0.009	0.039	0.019**	-0.006	0.016	0.015	0.018	-0.013	0.015
Appreciation and growth	0.000	0.010	0.009	0.021	-0.025	0.019	0.043	0.022**	-0.029	0.019
High appreciation Northeast	-0.014	0.011	-0.026	0.018	-0.047	0.021**	0.033	0.027	-0.012	0.020
High appreciation West	-0.019	0.010*	-0.007	0.020	-0.065	0.017***	0.037	0.018**	-0.039	0.018**
Large CBSAs - Change in log income										
Intercept	-0.039	0.016**	-0.063	0.026**	-0.011	0.030	-0.071	0.040*	-0.008	0.032
Base category (omitted)										
High growth	-0.013	0.022	-0.089	0.037**	0.005	0.044	-0.027	0.056	0.044	0.043
Appreciation and growth	0.014	0.020	-0.046	0.044	0.068	0.049	-0.063	0.051	0.104	0.042**
High appreciation Northeast	0.030	0.027	0.055	0.036	0.062	0.053	-0.029	0.066	0.030	0.058
High appreciation West	0.040	0.023*	-0.008	0.042	0.135	0.042***	-0.061	0.053	0.095	0.047**
N	30000		6200		6500		1300		11000	
Small CBSAs - Percent with income decrease										
Intercept	0.510	0.005***	0.512	0.011***	0.514	0.009***	0.531	0.012***	0.475	0.012***
Low appreciation, low growth (omitted)										
Low appreciation, high growth	0.007	0.012	-0.008	0.024	0.008	0.021	0.020	0.021	0.007	0.025
High appreciation, high growth	-0.010	0.014	-0.029	0.025	0.003	0.032	-0.016	0.029	0.009	0.025
High appreciation, low growth	-0.008	0.012	-0.033	0.021	-0.034	0.023	0.028	0.028	0.006	0.028
Small CBSAs - Change in log income										
Intercept	-0.023	0.014	-0.037	0.022*	-0.008	0.029	-0.097	0.030***	0.064	0.037*
Low appreciation, low growth (omitted)										
Low appreciation, high growth	-0.004	0.025	0.030	0.044	-0.011	0.046	0.034	0.050	-0.078	0.063
High appreciation, high growth	0.041	0.039	0.033	0.059	-0.040	0.081	0.136	0.073*	0.003	0.072
High appreciation, low growth	0.029	0.026	0.056	0.044	0.050	0.067	-0.019	0.062	0.036	0.067
N	15000		3700		3900		4100		3600	

Notes: The U.S. Census Bureau reviewed this data product for unauthorized disclosure of confidential information and approved the disclosure avoidance practices applied to this release. CBDRB-FY23-POP001-0045.
***p<.01, **p<.05, *p<.10

Table 6: OLS-Estimated Differences in Filtering Outcomes by Distance from the Central Business District.

	Pooled 1985-2021		1985-1993		1995-2003		2005-2013		2015-2021	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Pooled Large CBSAs - Percent with income decrease										
Intercept	0.513	0.005***	0.550	0.010***	0.486	0.010***	0.530	0.011***	0.483	0.010***
Inner ring (omitted)										
Middle ring	0.006	0.008	-0.017	0.015	0.011	0.016	0.031	0.017*	0.002	0.014
Outer ring	-0.002	0.007	-0.018	0.016	-0.011	0.013	0.027	0.016*	-0.001	0.014
Pooled Large CBSAs - Change in log income										
Intercept	-0.013	0.014	-0.084	0.020***	0.044	0.027	-0.052	0.034	0.049	0.025*
Inner ring (omitted)										
Middle ring	-0.032	0.020	0.025	0.033	-0.028	0.041	-0.097	0.047**	-0.030	0.038
Outer ring	-0.013	0.020	-0.007	0.029	0.009	0.037	-0.062	0.046	0.002	0.036
N	30000		6200		6500		1300		11000	
High Appreciation CBSAs - Percent with income decrease										
Intercept	0.508	0.013***	0.548	0.023***	0.457	0.022***	0.553	0.026***	0.472	0.023***
Inner ring (omitted)										
Middle ring	-0.006	0.016	-0.029	0.032	-0.001	0.035	0.023	0.038	-0.016	0.034
Outer ring	-0.017	0.018	-0.027	0.036	-0.032	0.032	0.010	0.037	-0.018	0.032
High Appreciation CBSAs - Change in log income										
Intercept	-0.003	0.036	-0.056	0.053	0.122	0.067*	-0.154	0.076**	0.073	0.062
Inner ring (omitted)										
Middle ring	0.000	0.044	0.016	0.070	-0.013	0.095	0.003	0.101	-0.003	0.092
Outer ring	0.011	0.044	-0.058	0.076	0.017	0.085	0.058	0.092	0.040	0.087
N	5700		1200		1300		1100		2100	

Notes: The U.S. Census Bureau reviewed this data product for unauthorized disclosure of confidential information and approved the disclosure avoidance practices applied to this release. CBDRB-FY23-POP001-0045.

***p<.01, **p<.05, *p<.10

Table 7: OLS-Estimated Differences in Filtering Outcomes by Housing Cost Tier.

	Pooled 1985-2021		1985-1993		1995-2003		2005-2013		2015-2021	
	%	SE	%	SE	%	SE	%	SE	%	SE
Percent with income decrease										
Intercept	0.524	0.006***	0.547	0.010***	0.501	0.011***	0.552	0.012***	0.483	0.011***
Highest cost tier (omitted)										
3rd cost tier	0.001	0.008	-0.018	0.014	-0.001	0.014	0.018	0.017	0.009	0.017
2nd cost tier	-0.011	0.009	-0.021	0.014	-0.004	0.016	-0.007	0.019	-0.015	0.019
Lowest cost tier	-0.024	0.009***	-0.024	0.016	-0.034	0.014**	-0.024	0.017	-0.015	0.019
Change in log income										
Intercept	-0.048	0.013***	-0.103	0.019***	-0.001	0.026	-0.112	0.032***	0.052	0.027*
Highest cost tier (omitted)										
3rd cost tier	0.003	0.020	0.023	0.028	0.011	0.035	-0.019	0.047	0.000	0.044
2nd cost tier	0.003	0.021	0.022	0.030	-0.019	0.037	0.018	0.047	-0.004	0.046
Lowest cost tier	0.066	0.021***	0.076	0.034**	0.129	0.038**	0.054	0.043	-0.020	0.049
N	33500		8700		8400		7800		8500	

Notes: The U.S. Census Bureau reviewed this data product for unauthorized disclosure of confidential information and approved the disclosure avoidance practices applied to this release. CBDRB-FY23-POP001-0045.

***p<.01, **p<.05, *p<.10

Table A-1: Variation in Filtering Estimates by Time Period.

	Pooled 1985-2021		1985-1993		1995-2003		2005-2013		2015-2021	
	Est	SE	Est	SE	Est	SE	Est	SE	Est	SE
Percent with income decrease	50.8%	0.25%	52.6%	0.47%***	49.6%	0.48%***	53.9%	0.51%***	48.0%	0.52%***
Mean change in log income	-0.011	0.006	-0.055	0.010***	0.025	0.012***	-0.083	0.013***	0.054	0.013***
N	50500		12000		12000		11000		15500	

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***p<.01, **p<.05, *p<.10; asterisks indicate whether measures are statistically different from the estimate for the prior period. Asterisks for 1985-1993 compare to the pooled sample for 1985-2021.

Table A-2: OLS-Estimated Differences in Filtering Outcomes by Metropolitan Area Type.

	Pooled 1985-2021		1985-1993		1995-2003		2005-2013		2015-2021	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Large CBSAs - Percent with income decrease										
Intercept	0.518	0.007***	0.541	0.013***	0.510	0.013***	0.527	0.013***	0.502	0.014***
Base category (omitted)										
High growth	0.003	0.009	0.041	0.019**	-0.002	0.019	0.014	0.019	-0.016	0.018
Appreciation and growth	-0.002	0.010	0.009	0.021	-0.021	0.020	0.038	0.021*	-0.031	0.020
High appreciation Northeast	-0.020	0.011*	-0.035	0.020*	-0.047	0.020**	0.021	0.023	-0.016	0.022
High appreciation West	-0.023	0.010**	-0.013	0.019	-0.067	0.019***	0.029	0.021	-0.039	0.020**
Large CBSAs - Change in log income										
Intercept	-0.038	0.017**	-0.077	0.025**	0.000	0.031	-0.082	0.039**	-0.005	0.034
Base category (omitted)										
High growth	-0.004	0.024	-0.089	0.039**	-0.004	0.045	-0.027	0.057	0.053	0.043
Appreciation and growth	0.022	0.025	-0.034	0.042	0.049	0.051	-0.050	0.054	0.106	0.047**
High appreciation Northeast	0.047	0.028*	0.078	0.039**	0.061	0.055	0.005	0.061	0.040	0.060
High appreciation West	0.051	0.024*	0.008	0.038	0.141	0.046***	-0.030	0.054	0.083	0.047*
N	30000		6200		6500		1300		11000	
Small CBSAs - Percent with income decrease										
Intercept	0.504	0.006***	0.511	0.012***	0.515	0.011***	0.527	0.012***	0.471	0.014***
Low appreciation, low growth (omitted)										
Low appreciation, high growth	0.010	0.012	-0.005	0.023	0.002	0.022	0.023	0.022	0.017	0.026
High appreciation, high growth	-0.006	0.014	-0.026	0.027	-0.001	0.027	-0.014	0.027	0.016	0.027
High appreciation, low growth	-0.006	0.013	-0.037	0.024	-0.027	0.024	0.024	0.024	0.004	0.028
Small CBSAs - Change in log income										
Intercept	-0.019	0.016	-0.039	0.023*	-0.011	0.029	-0.093	0.032***	0.055	0.036
Low appreciation, low growth (omitted)										
Low appreciation, high growth	-0.012	0.031	0.023	0.046	0.003	0.054	0.028	0.060	-0.082	0.069
High appreciation, high growth	0.055	0.037	0.025	0.064	-0.037	0.058	0.120	0.070*	0.053	0.077
High appreciation, low growth	0.037	0.029	0.074	0.044*	0.037	0.059	0.002	0.055	0.053	0.068
N	15000		3700		3900		4100		3600	

Notes: The U.S. Census Bureau reviewed this data product for unauthorized disclosure of confidential information and approved the disclosure avoidance practices applied to this release. CBDRB-FY23-POP001-0045.
***p<.01, **p<.05, *p<.10

Table A-3: OLS-Estimated Differences in Filtering Outcomes by Housing Cost Tier.

	Pooled 1985-2021		1985-1993		1995-2003		2005-2013		2015-2021	
	%	SE	%	SE	%	SE	%	SE	%	SE
Percentage with income decrease										
Intercept	0.519	0.006***	0.547	0.011***	0.500	0.011***	0.553	0.012	0.480	0.014
Highest cost tier (omitted)										
3rd cost tier	0.001	0.009	-0.019	0.015	-0.002	0.016	0.014	0.017	0.010	0.019
2nd cost tier	-0.010	0.009	-0.018	0.015	0.000	0.016	-0.015	0.017	-0.009	0.019
Lowest cost tier	-0.025	0.009***	-0.024	0.016	-0.039	0.016**	-0.029	0.017	-0.015	0.020
Change in log income										
Intercept	-0.047	0.014***	-0.111	0.019***	-0.003	0.028	-0.129	0.032***	0.048	0.030*
Highest cost tier (omitted)										
3rd cost tier	0.023	0.021	0.031	0.028	0.026	0.040	0.002	0.046	0.036	0.048
2nd cost tier	0.010	0.020	0.025	0.030	-0.023	0.039	0.049	0.045	-0.007	0.046
Lowest cost tier	0.072	0.021***	0.079	0.032**	0.142	0.042**	0.082	0.047	-0.010	0.050
N	33500		8700		8400		7800		8500	

Notes: The U.S. Census Bureau reviewed this data product for unauthorized disclosure of confidential information and approved the disclosure avoidance practices applied to this release. CBDRB-FY23-POP001-0045.
***p<.01, **p<.05, *p<.10