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Filtering of Apartment Housing between 1980 and 2018

SUBMITTED BY

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Dowell Myers is a professor of policy, planning, and demography in the Sol Price School of Public Policy at USC. He is a leading expert on changing demographics in California and the United States and how those dynamics interact with markets, politics and policy making. Dr. Myers is the most recognized specialist in the U.S. on how demographic trends drive housing and real estate. He was designated Dean of Demographics for HanleyWood's HIVE conference (2016), served 8 years as an Academic Fellow of the Urban Land Institute, and also served on the professional advisory committee to the Census Bureau. Dr. Myers has been the leading scholar of housing needs in California since the 1990s. As part of the California experience, he grew to be an expert on immigration, assimilation, and the dynamics for housing, including both overcrowding and homeownership. Dr. Myers was recently recognized with the Dale Prize for Excellence in Planning Scholarship (2017) and his studies on demographics and housing have twice received the Best Article award from the Journal of the American Planning Association. Dr. Myers holds his PhD from MIT, a Master of City Planning from UC-Berkeley, and a BA from Columbia University. Many of his publications are available at https://sites.usc.edu/popdynamics/.

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EXECUTIVE SUMMARY

The operation of the "filtering" process in the housing market has recently received new attention in light of the nation's intensifying housing crisis following the Great Recession. This long-standing mechanism for providing affordable housing to lower-income households operates through the aging and obsolescence of housing over long periods of time.

This study of apartment housing (defined as rental units in structures with five or more units) covers the time period of 1980 to 2018 and investigates rental occupancy trends in the 100 largest metropolitan areas. Primary data sources are the Census Bureau's decennial census and American Community Survey, supplemented by HUD databases of subsidized housing.

Filtering is measured here by the growing share of units in aging apartments that were occupied by low-income renters, defined as those whose household income is less than or equal to 50 percent of the median in their metropolitan area of residence.

Major findings include:

1. Filtering occurred at different rates in each decade but produced rising shares of low-income occupancy until the Great Recession, after which the low-income occupancy declined (see Exhibit 4). In 21 years, from 1990 to 2011, filtering increased the low-income occupancy share by an added 11.3 percent of 1960s built apartments, 8.6 percent of 1970s apartments and 10.3 percent of 1980s apartments. From 2011 to 2018, low-income share reversed, declining by 3.8 percent, 6.0 percent and 4.4 percent, respectively (see Exhibit 5).

2. Overall rents rose continuously over the study period, because each newly built vintage entered the market with ever higher rents. However, within each vintage, median rents generally fell between 1990 and 2006 (adjusted for inflation) but rose sharply after the recession (see Appendix A).

3. Rising rents in the market exceeded income changes of renters, and so affordability broadly declined. Even though the older units provided the greatest refuge for low-income renters, their rent-to-income ratio grew higher each decade (see Appendix D).

4. A continued stream of new construction, even if it enters in higher price brackets, is important to the success of filtering in providing low-income shelter. The sharp reversal of filtering after 2011 corresponded to the sluggish increases in housing supply despite resurgent job growth in metropolitan areas (see Appendix C).

5. The decline in homeownership rates was an added deterrent to filtering in the post-recession era, in addition to the slow rate of construction, because so many would-be homeowners were diverted into competition for rental housing. Every one percentage point decline in homeownership rates among the 25-to-34 age group equated to a 0.4 percentage point decline in the rate of filtering (see Exhibit 12).

6. Overall, nationwide, filtering in good years produced a substantial boost in housing opportunity for low-income households in apartments. A total of 69,000 additional low-income occupied units was generated annually between 2000 and 2006 in the existing stock, whereas 22,000 units were added annually by growth in HUD-subsidy programs for apartment housing supply, with another 92,000 low-income (<50 percent of area median income) units added annually through LIHTC tax subsidies. After 2011, the filtering growth in opportunity turned negative and the federal subsidized supply programs also were greatly diminished (see Exhibit 14).

1. INTRODUCTION

This research project "Filtering of Apartment Housing Between 1980 and 2018" summarizes the key findings on apartment filtering in the United States. This project has the overall purpose of estimating the filtering of apartments to provide housing opportunities for lower-income Americans.

In this study, filtering is defined and measured by its consequences for very low-income households, defined by HUD as having household income no more than 50 percent of the median in the local metropolitan area. Filtering occurs as housing units grow older and lower-income tenants gain an increasing share of the units. Apartment filtering is measured by the increase over time in the share of apartments (rental units in five or more unit structures) that are occupied by very low-income households.

National and metropolitan-level trends in apartment filtering are estimated on the basis of a vintage longitudinal approach. We find considerable differences in apartment filtering over different periods since 1980, including more rapid filtering in the 1980s than other decades and reversed filtering (loss of low-income opportunity) since 2012. Exploiting the variation observed across the 100 largest metropolitan areas, we estimate the effects of key contextual variables in different markets, including new construction, job growth and falling rates of homeownership. We find an expected, strong positive effect of new construction on apartment filtering, as well as an expected, strong effect of falling homeownership rates among young adults, which threw more middle-income households into rental competition (Myers, Painter, Lee and Park 2016). In the report, we also assess the relative importance of filtered market-rate apartments for low-income households relative to the number of federally subsidized units. The downturn in construction is shown to result in major loss of low-income housing opportunity.

Section 2 defines and tests key concepts in the measurement of filtering. Section 3 describes the sample of 100 largest metropolitan areas in the United States and presents metropolitan-level filtering of apartment housing in terms of gains or losses of occupancy by low-income renters. We visually summarize the different rates of apartment filtering since 1980 for the 50 largest metropolitan areas. This section also explores differences by apartment size, as measured by number of bedrooms. Next, in Section 4, we describe data on contextual factors that could explain the differences in filtering rates between metropolitan areas, including rates of new construction, job growth, and shifts from homeownership to renting. A series of regression estimations are constructed and evaluated.

Section 5 then assesses the magnitude of housing opportunities yielded through filtering compared to opportunities supplied in subsidized housing units. Section 6 concludes with a summary of findings and a discussion of policy implications stemming from our findings.

2. VINTAGES OF APARTMENT UNITS AND FILTERING

Vintages and Aging of Units

Filtering is considered to be a process occurring as dwellings age over time. To measure this aging process, we define apartment units as renter-occupied housing units in residential structures with five or more units (hereafter, apartments) by their decade of construction (vintages, hereafter) and then compare the changes from one survey year to the next as the vintages grow older. We make use of a specific variable that is based on survey responses to the question: "About when was this building first built?" Although these responses are subject to respondent error, particularly for properties that were built at the very beginning or end of decade, the vintage identification is reasonably stable over time. Vintage measurement is commonly used in urban analysis to identify panels of housing units, such as in a very recent rent control study published in the *American Economic Review*.[1]

We first compare national data over time and show that the number of apartment units recorded in each vintage remains fairly stable, with some exceptions. For this we focus primarily on seven vintages of multifamily rentals: built before 1960, or in the 1960s, 1970s, 1980s, 1990s, 2000s and post-2010. As shown in Exhibit 1, the number of units in each vintage is relatively consistent over time, with declines registered in the oldest vintage (pre-1960), where demolitions are most likely. We also observe a greater decline in the count of units in a vintage in the second decade than in later decades, such as the 1970s vintage after 1980 or 1980s vintage after 1990. Roughly one-tenth to one-seventh of units in a vintage appear to have been assigned to other vintages that are newer or perhaps older. Thereafter, the changes are more stabilized.

Exhibit 1. Count of Apartment Units by Vintage of Structure, United States, 1980 to 2018

	1980	1990	2000	2006	2011	2018
5+ MF Renter-occupied Units						
Pre-1960 Vintage	4,952,600	4,217,607	4,098,506	3,869,210	3,837,912	3,806,736
1960s Vintage	3,195,520	2,588,582	2,501,036	2,116,979	2,118,924	2,150,387
1970s Vintage	4,107,780	3,712,306	3,797,513	3,429,474	3,422,731	3,542,812
1980s Vintage		3,679,640	3,110,599	2,816,844	2,828,502	3,005,402
1990s Vintage			2,422,626	2,125,231	2,286,263	2,749,202
2000s Vintage				1,666,136	2,741,167	2,309,909
Post-2010 Vintage					120,663	1,984,040
Sum in Absolute Count	12,255,900	14,198,135	15,930,280	16,023,874	17,356,162	19,548,488

Notes: Universe is renter-occupied 5+ multifamily housing units in the United States. A sharp increase of 2000s vintage between 2006 and 2011 is due to new constructions from 2006 through 2009. For the same reason, another sharp increase of post-2010 vintage is found between 2011 and 2018.
Sources: 1980, 1990 and 2000 Decennial Census; 2006, 2011 and 2018 American Community Survey 1-year IPUMS Microdata files (Ruggles et al., 2019).

[1] Rebecca Diamond, Tim McQuade, and Franklin Qian, "The Effects of Rent Control Expansion on Tenants, Landlords, and Inequality: Evidence from San Francisco," American Economic Review 2019, 109(9): 3365–3394.

Analysis to follow is built upon the universe of rental apartments in each declared vintage; however, measurement of low-income occupancy shares within rental apartments of each vintage provides a substantial buffer from the variability of the size of the universe.

Income Level of Apartment Tenants

Renter households who earn no more than 50 percent of their metropolitan area median household income are described by HUD as "very low-income," and they are the primary target population of major federal rental-assistance programs (Schwartz, 2015). Exhibit 2 shows four exclusive income groups categorized on the basis of the national[2] median household income of $61,000 in 2018, including high-income earning more than 120 percent of median household income, middle-income earning 80-120 percent of median, low-income earning 50-80 percent of median and very low-income earning 0-50 percent of median. Our particular interest is very low-income households who earn $30,500 or less per year and are in the greatest need of filtering benefits to secure a place to live. As will be shown, this group lives disproportionately in multifamily rentals.

Exhibit 2. Income Group and Corresponding Dollar Ranges of Income, United States, 2018

	(a) % Range Relative to Median Income	(b) $ Range of Income (2018$)
Median HH Income = $61,000		
High-income HH	Above 120% of Median	Above 73,200
Middle-income HH	80 to 120% of Median	48,800 to 73,200
Low-income HH	50 to 80% of Median	30,500 to 48,800
Very Low-income HH	0 to 50% of Median	0 to 30,500

Notes: Universe is occupied housing units in the nation. HH is household. Income groups are exclusive to each other. Our analysis is based onthe Harvard Joint Center's approach to using the "not computed" subgroup and the "greater than" treatment of the income thresholds (for details see footnote 2 on page 165 of Myers & Park, 2019).

Sources: 2018 American Community Survey 1-year IPUMS Microdata files (Ruggles et al., 2019).

Exhibit 3 shows lower-income households in context of all households in the nation. We break down all households in the United States by the share falling into each income level in 1980, 1990, 2000, 2006, 2011 and 2018. Panel (a) shows apartment housing, while panels (b) and (c) show the other rental housing (single-family, duplex to fourplex, and mobile homes) and owner-occupied housing, respectively. The bottom panel (d) sums these shares to show the relative income distribution of all households in the nation.

By far the largest shares of households live in owner-occupied housing (60 percent or higher). The apartment renters (MF 5+) comprise a little less than half of the total renters. As a share of total households—both tenures and all structure types combined—the apartment share fell to a low in 2006 (14.4 percent) at the peak of the homeownership bubble but then rapidly rebounded to its highest share (16.1 percent) in 2018 (Exhibit 3, panel a).

[2]For simplicity, here we use national median household income. Metropolitan-specific local median household incomes are used in the following sections on metropolitan areas.

Exhibit 3. Income Group Share of All Households, Grouped by Tenure and Structure Type, United States, 1980 to 2018

	1980	1990	2000	2006	2011	2018
Median HH Income (2018$)	51,322	57,745	61,028	60,349	56,377	61,000
(a) 5+ MF Renter-occupied Units						
High-income HH	3.1	3.2	3.1	2.7	2.9	3.7
Middle-income HH	3.0	2.9	2.7	2.4	2.3	2.7
Low-income HH	3.2	3.1	3.1	2.8	2.8	2.9
Very Low-income HH	5.9	6.3	6.3	6.5	7.0	6.9
Sum in %	**15.2%**	**15.5%**	**15.1%**	**14.4%**	**15.1%**	**16.1%**
Sum in Absolute Count	**12,255,900**	**14,198,135**	**15,930,280**	**16,023,874**	**17,356,162**	**19,548,488**
(b) Other Renter-occupied Units						
High-income HH	4.2	4.6	4.3	3.7	4.5	5.0
Middle-income HH	4.1	4.0	3.6	3.3	3.4	3.6
Low-income HH	4.2	4.1	3.9	3.8	4.0	3.8
Very Low-income HH	7.2	7.5	6.9	7.5	8.3	7.5
Sum in %	**19.8%**	**20.3%**	**18.7%**	**18.4%**	**20.2%**	**19.9%**
Sum in Absolute Count	**15,906,920**	**18,626,037**	**19,731,276**	**20,518,715**	**23,259,246**	**24,176,865**
(c) Owner-occupied Units						
High-income HH	32.8	31.9	33.6	34.4	33.4	33.6
Middle-income HH	12.4	12.1	12.6	12.4	11.3	11.0
Low-income HH	8.5	8.8	9.4	9.4	9.1	8.5
Very Low-income HH	11.3	11.4	10.6	11.1	10.9	10.9
Sum in %	**65.0%**	**64.2%**	**66.2%**	**67.3%**	**64.7%**	**64.0%**
Sum in Absolute Count	**52,304,180**	**58,922,248**	**69,818,545**	**75,074,799**	**74,376,307**	**77,794,832**
(d = a + b + c) All Occupied Units						
High-income HH	40.1	39.7	41.0	40.8	40.8	42.2
Middle-income HH	19.5	19.0	18.9	18.2	17.1	17.3
Low-income HH	15.9	16.0	16.3	16.0	15.9	15.2
Very Low-income HH	24.4	25.3	23.8	25.0	26.2	25.3
Sum in %	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Sum in Absolute Count	**80,467,000**	**91,746,420**	**105,480,101**	**111,617,388**	**114,991,715**	**121,520,185**

Notes: Universe is households living in occupied housing units in the United States. HH is household. 5+ MF is multifamily structure with fiveor more units. Income groups are exclusive to each other, including high-income group earning 120 percent+ of median HH income, middle-income earning 80-120 percent of median, low-income earning 50-80 percent of median and very low-income earning 0-50 percent of median. Median HH income is inflation-adjusted to 2018$ by the U.S. Bureau of Labor Statistics national annual consumer price index (CPI) all items, which is 1.000 in 2018, 1.116 in 2011, 1.246 in 2006, 1.458 in 2000, 1.921 in 1990 and 3.047 in 1980.
Sources: 1980, 1990 and 2000 Decennial Census; 2006, 2011 and 2018 American Community Survey 1-year IPUMS Microdata files (Ruggles et al., 2019).

This underscores the growing importance of multifamily apartments as shelter for Americans. Both the highest- and lowest-income groups have a greater occupancy in apartments (3.7 percent and 6.9 percent in 2018, respectively) than any time since 1980. In fact, the very low-income group comprises a larger share of multifamily residents in 2018 than all others, 43 percent (= 6.9 percent / 16.1 percent).

The overall income distributions found in each decade for all households (without disaggregation by tenure) are remarkably consistent. This stability results from benchmarking each income group to the median household income, which is itself rising or falling. Against this stability, we can observe some relative shifts toward lower-income groups over time. If this shift is slight in the overall population, it is substantially more prominent in apartments, especially those that are in aging vintages (as shown later).

Definition of Filtering and its National Trend

We measure filtering of apartment housing in terms of gains or losses of low-income occupancy. As dwellings age and obsolesce, their relative quality declines, as does the rents they command, and, accordingly, so does the income of the occupants.[3] For lack of sufficient supply, these typical patterns may be blocked as prices rise, instead of decline, and households may search downward to lower-quality housing that is more affordable. In effect, housing units are elevated into a higher-income bracket. That can be described as reversed filtering or housing units filtering upward.[4]

Filtering is in fact multifaceted, involving incomes, rents, housing quality, affordability and possibly including education, class or social group membership. The correlation of these dimensions greatly complicates their inclusion in the same analysis. In the debate over whether filtering “works,” the key indicator seems to be whether or not lower-income households benefit by gaining greater housing opportunities over time. Hence, we have elected to focus on the bottom-line criterion: how much does the low-income share of rental occupancy increase over time as an apartment vintage grows older?

We measure the proportion of apartment housing that is occupied by low-income households, defined as renters whose household income is half or less of their metropolitan area median household income.[5] If a greater share of apartments in a given vintage becomes occupied by low-income renters, we interpret that as a *housing access benefit* due to filtering. As a cross check, we also trace changes in the median rent payment, including the contract rent and utilities, to see if older apartments grow cheaper over time. If so, that might be termed a *rental affordability benefit* of apartment filtering.

However, the notion of “affordability” may be an elusive goal for filtering to achieve. The inflation-adjusted increases in rents have far outpaced the growth of incomes in recent decades. Between 2000 and 2016, the median gross rent in the nation increased 63.3 percent, while the median household income of renters grew only 35.9 percent (Myers and Park, 2019, Table 4). A new, more basic concern has pushed to the fore in recent years. In addition to affordability pressures, renters now face a more basic obstacle, a severe shortage of housing opportunities. There is simply an inadequate supply of housing to accommodate all the households who may be seeking apartments, no matter the price (Harvard JCHS, 2020). As a result, household formation is being cut back, young people are staying longer with roommates or in their parents’ spare bedrooms, and more people are becoming literally homeless.

[3] The early definition by Ratcliff (1949) is widely cited: “This process … is described most simply as the changing of occupancy as the housing that is occupied by one income group becomes available to the next lower income group as a result of decline in market price …” Notice that this definition comprises three interacting components: change in occupancy (turnover); declining price; and declining income.

[4] For a general discussion of forces and outcomes in filtering, see filtering explanation in the Encyclopedia of Housing (Myers and Mawhorter, 2012).

[5] We choose to use the generic term “low income” here, although in HUD terms this would be the “very low income” category.

Our preferred measure of filtering—the increased low-income share of a vintage as years pass and it grows older—is focused on access to housing, no matter the price. We would expect to see a higher share that is low income in vintages that are older, and over time we would expect to see the low-income share rising in each vintage as it grows older. Bear in mind that our measure of 'low income' is standardized to the median in each local area, so that the definition is always relative to the area median income. We are looking at the relative group whose income is less than half of the level of the median. Filtering occurs on this relative scale as people sort themselves into units of hierarchically ranked quality in each metro area.

Exhibit 4 shows the level of low-income occupancy in each vintage of apartments and also the longitudinal trend for each vintage, aggregated for the largest 100 metropolitan areas[6] between 1980 and 2018. To reflect different metropolitan sizes, we average low-income share and gross rents across the 100 metros with weights for total number of households in each metro.[7] As expected, the older vintages provide housing opportunities to a larger share of tenants who are low income. The oldest vintage held a noticeably larger share in 1980 than newer units, and that remains true in 2018. But within each vintage that grows older over the 31 years from 1980 to 2011, the low-income share rose markedly. In the 1960s vintage, the access by low-income renters increased by +18 percentage points and in the 1970s vintage by +16 points. Also noteworthy is that the 1970s, 1980s and 1990s vintages all provided shelter for a 36 percent share of their tenants when they were newly built, before increasing their share in decades to follow.

The record after 2011 is extremely different. All vintages held their highest shares of low-income tenants in 2011, at the depths of the Great Recession, but thereafter their low-income share decreased. This downturn occurred in parallel across the vintages, an unprecedented trend. Explaining this reversal is a major focus of sections to follow.

The trend in rent payments deserves comparison (Appendix A). In the left panel (a), for all vintages combined, we see that rents rapidly increased since 1980, with pauses in the 1990s and during the Great Recession, but that was followed by an even greater upward surge after 2011 (all rents are adjusted to 2018 dollars).

The analysis of specific vintages is given in the right panel (b) of Appendix A. Most vintages commanded declining rents from 1990 through 2006, but all vintages participated in the rent boom after 2011. It is also worth noting that the aggregate rent trend in panel (a) is much steeper than the trend witnessed within each vintage. That is a reflection of the higher rents added by each new wave of construction. Older and cheaper rentals became a smaller share of the stock as new construction was completed, and the average rents climbed upward.

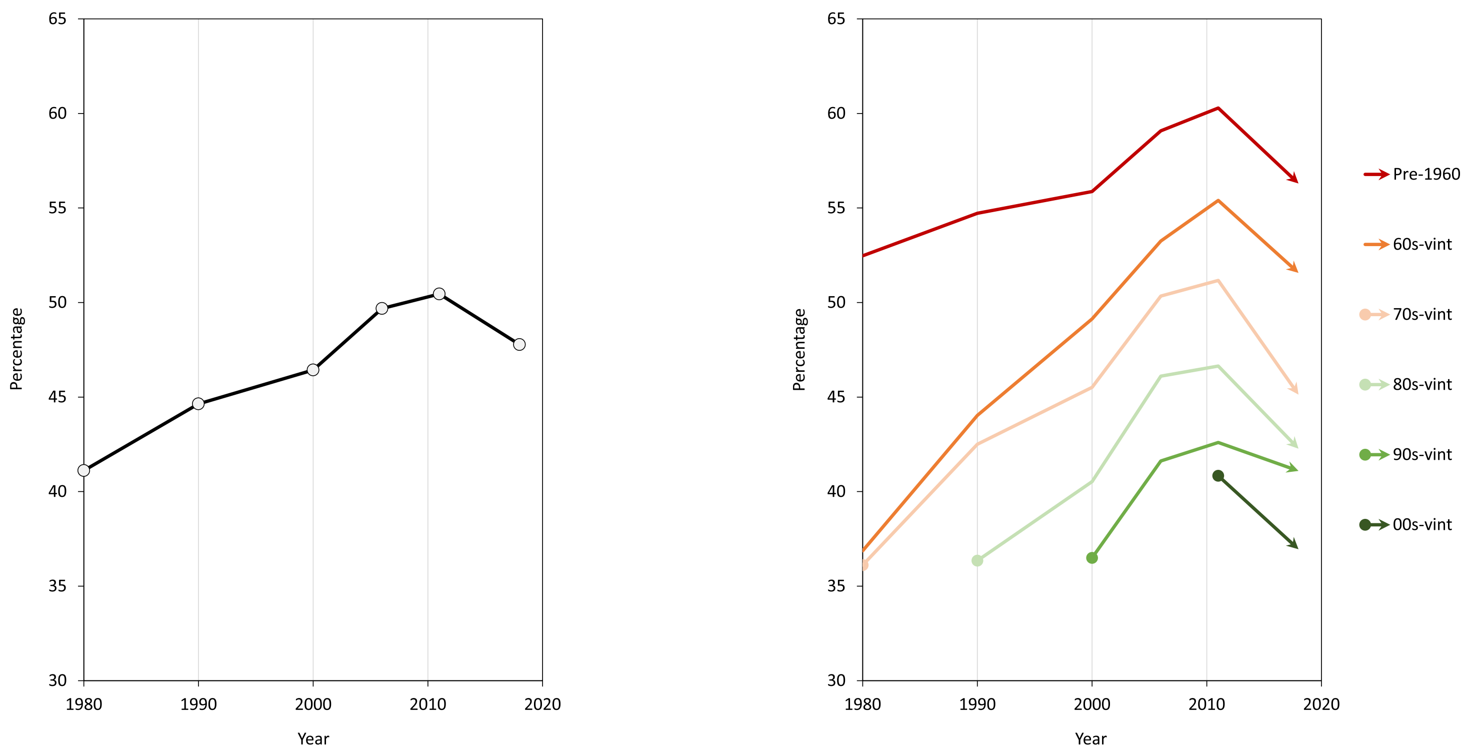
Overall, the rental trend is supportive of the filtering story. Newer vintages command higher rents and provide shelter to fewer low-income renters. The fact that rents were so stable from 1990 through 2011 did not prevent filtering, because low-income tenants paid higher shares of their incomes for rent in order to gain access to better housing. As a result of these rental increases, excessive rent burden increased steadily since 1970, afflicting not only low-income renters but middle-income groups as well (Harvard JCHS, 2020).

[6] The sample of the 100 largest metropolitan areas is described in the following section, and its full list is available in the Appendix.

[7] We find the use of a weight variable results in different average value, but it does not largely differ from unweighted average. We use the number of households as our weight variable for metro size among alternatives including population, renter households and apartment renter households.

Exhibit 4. Vintage Longitudinal Trend in Low-income Share of Apartment Housing, 100 Largest Metropolitan Areas, 1980 to 2018

(a) All Vintages Combined **(b) By Vintage**



Notes: Universe is renter-occupied housing units in structures with fiveor more units in each metro area. Low-income households are defined as earning half or less of their metropolitan median household income in each survey year. Trend lines are the average of 100 largest metro areas, weighted by absolute count of households in each metro area and survey year. Panel (a) includes post-2010 vintage in 2011 and 2018 data.
Sources: 1980, 1990 and 2000 Decennial Census; 2006, 2011 and 2018 American Community Survey 1-year IPUMS Microdata files (Ruggles et al., 2019).

A summary of the changes in each time interval, along with significance test result, is provided in Exhibit 5. In general, the greatest changes in low-income occupancy are observed in the 1960s vintage of apartment units and least in the very broad vintage of all units built before 1960. However, overall, the degree of change each decade and its direction are very similar across the vintages. Of greatest note, in contrast to the strong, prevalent filtering observed before the Great Recession, changes in low-income occupancy were not significant during the bust and then significantly reversed to negative during the post-recession recovery period. These similarities across the vintages are reflected in the parallel lines of filtering change each decade shown previously (Exhibit 4).

Exhibit 5. Changes in Low-income Share Occupancy of Apartment Vintages, 100 Largest Metropolitan Areas, 1980 to 2018

(a) Low-income Share Occupancy (%) of Apartment Vintages											
	1980	1990		2000		2006		2011		2018	
Pre-1960 Vintage	52.5	54.7		55.9		59.1		60.3		56.3	
1960s Vintage	36.9	44.0		49.1		53.3		55.4		51.6	
1970s Vintage	36.1	42.5		45.5		50.3		51.2		45.1	
1980s Vintage		36.3		40.5		46.1		46.6		42.3	
1990s Vintage				36.5		41.6		42.6		41.1	
2000s Vintage								40.8		37.0	
All Vintages Combined	41.1	44.6		46.4		49.7		50.5		47.8	

(b) Difference from Previous Observation Year										
	1980–1990		1900–2000		2000–2006		2006–2011		2011–2018	
Pre-1960 Vintage	2.2	***	1.2	*	3.2	***	1.2		−4.0	***
1960s Vintage	7.2	***	5.1	***	4.1	***	2.1	**	−3.8	***
1970s Vintage	6.4	***	3.0	***	4.8	***	0.8		−6.0	***
1980s Vintage			4.2	***	5.6	***	0.5		−4.4	***
1990s Vintage					5.1	***	1.0		−1.5	
2000s Vintage									−3.9	**
All Vintages Combined	3.5	***	1.8	***	3.3	***	0.8		−2.7	***

Notes: + = $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Universe is renter-occupied 5+ multifamily housing units in each of the 100 largest metropolitan areas. Low income is defined as earning half or less of metropolitan median household income in each year. The t-tests for statistical differences in low-income occupancy and gross rent of vintage apartment were performed by using the sample of the largest 100 metro areas. The category of All Vintages Combined includes post-2010 vintage in 2011 and 2018 data.
Sources: 1980, 1990 and 2000 Decennial Census; 2006 through 2018 American Community Survey 1-year IPUMS Microdata files (Ruggles et al., 2019).

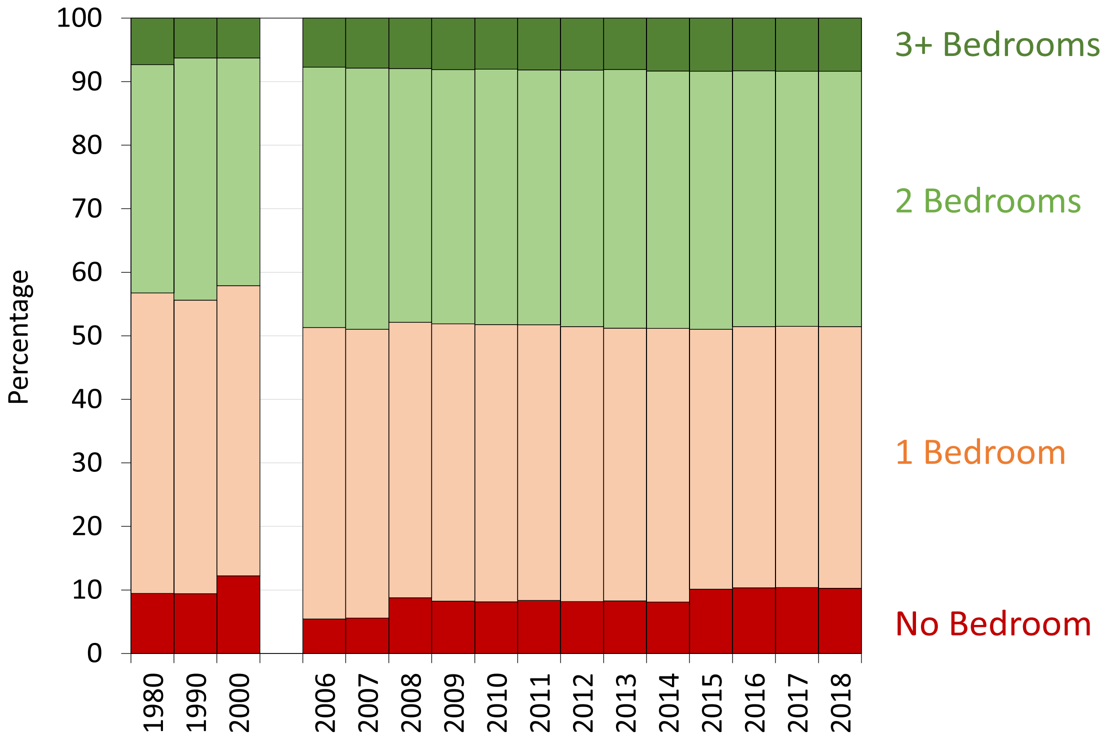
Filtering of 2-Bedroom and Other Size Apartments

Trends of apartment filtering may differ by the number of bedrooms.[8] If there is a substantial shift over the decades toward larger or smaller apartments, that could alter the estimated trend in filtering. Fortunately, our base analysis shows a very constant national bedroom mix of apartment units since 1980 (Exhibit 6). The 2-bedroom share of apartment units in the nation has long been around 40 percent of all apartment housing units, while another 40 percent is accounted by

[8] Our source data does not enable us to distinguish apartments by other size measures, such as square footage or number of bathrooms.

1-bedroom. The remaining 20 percent is allocated equally between studios and 3 or more bedroom units. Both rent and tenant's income are often lower in 1-bedroom and studio types than 2-bedroom and 3 or more bedroom types. Thus, we expect that a greater share of smaller apartment units than 2-bedroom units would house low-income residents.

Exhibit 6. Percent of Apartments by Number of Bedrooms, United States, 1980 to 2018

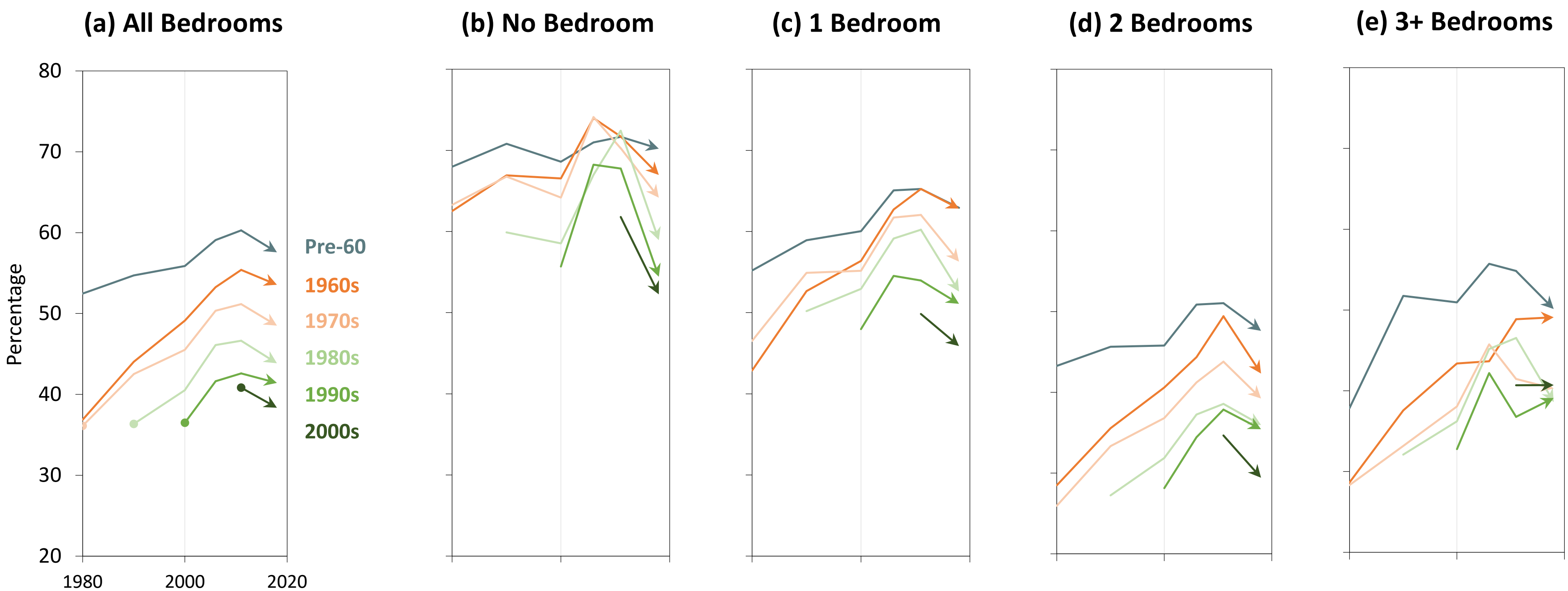


Sources: 1980, 1990 and 2000 Decennial Census; 2006 through 2018 ACS IPUMS Microdata files.

Exhibit 7 shows low-income occupancy of apartment housing units by number of bedrooms and compared to the trends for all apartment units (Exhibit 7 panel a), as displayed previously in Exhibit 4. A substantially greater share of studios is occupied by low-income residents – roughly 20 percent higher in all vintages (panel b). Nearly two thirds of the older studios, such as pre-1960, 1960s and 1970s, have been occupied by low-income residents since 1980 or earlier. Given that studios accounted for only 10 percent of national apartment stock, however, the filtering effect of studios may not be very large in absolute count.

The most important role in filtering is played by 1- and 2-bedroom units because they account for 80 percent of the nation's apartment stock. While the low-income share of 1-bedroom units (panel c) is around 10 percent *higher* than all bedroom types combined, in virtually every vintage, low-income occupancy of 2-bedroom units (panel d) is about 10 percent *lower* than all apartments combined. Nonetheless, despite this difference in the level of low-income occupancy, the *slopes* of the filtering trend (i.e., the change in low-income occupancy over time) are very similar between the 1-bedroom and 2-bedroom apartments and closely match the slopes observed for all apartments combined.

Exhibit 7. Low-income Occupancy of Apartment Units by Number of Bedrooms, 100 Largest Metropolitan Areas, 1980 to 2018



Sources: 1980, 1990 and 2000 Decennial Census; 2006 through 2018 ACS IPUMS Microdata files.

3. CHANGES OVER DECADES AND DIFFERENCES ACROSS METROPOLITAN AREAS

Sample of 100 Largest Metropolitan Areas

We identify apartment units in each metropolitan area by using the U.S. Census Bureau's decennial census and American Community Survey (ACS) data, organized in the Integrated Public Use Microdata Samples (IPUMS) (Ruggles et al., 2019).

Analysis focuses on a sample of the 100 most populous metropolitan areas, which are specified according to the geographic definitions used in the 2010 census. (See Appendix E for the full list of the 100 metro areas and their constituent counties.) The largest metropolitan area is New York, which had 2,303,152 apartment units in 2018, and the 100th is Santa Rosa, CA, which had 39,931 apartment units in 2018. We create a standardized set of the 100 metros with consistent geographic boundaries over time. To build these consistent-boundary metro areas in all data years since 1980, we reassign Public Use Microdata Areas (PUMAs) proportionally into metro boundaries by using weights of total households at the census-tract level.

Metropolitan Trend in Apartment Filtering Across Different Decades

Despite the national average trend in apartment filtering, low-income occupancy gains were clearly substantially greater in some metropolitan areas than in others (Appendix B). Also, the regional differences were greater in some decades (or semi-decades) than in others since 1980. In this section, we descriptively—and visually—display the rates of filtering each decade in the 50 largest metro areas. For this purpose, we rank the metros from high to low within each of the four census regions, oriented in west-to-east perspective (West on the left, located next to the Pacific, and the East and South on the right, next to the Atlantic).

For comparison purposes, a single composite measure rather than multiple individual vintage measures may be effective when comparing 50 metro areas, separately for different decades (or semi-decades). Thus, we calculate a composite annual rate of filtering in apartment housing units in each metro area, separately for each decade (or semi-decade). It excludes construction after the beginning of each decade (or semi-decade) to focus on existing units. For example, in the Los Angeles metro area (combination of LA and Orange counties) during 1990s, low-income share occupancy of existing (built before 1990) apartment units was 37.3 percent (=386,000 low-income-occupied apartment units divided by 1.0 million apartment units) in 1990, which increased to 40.5 percent (= 411,000 divided by 1.0 million) in 2000. The increase of 3.2 percentage points was divided (annualized) by 10 resulting in a 0.32 percentage point change per year during the 1990s, which is displayed as yellow column in Exhibit 8. We repeat this calculation to every metro, separately for different decades (or semi-decades).

The rates of filtering in apartment housing units in the 1980s were strong and widely prevalent across the large metros (Exhibit 8). Apartment units in the southern metros, such as Dallas and Atlanta, were particularly successful in transferring one percent of their apartment stock to low-income residents every year in the 1980s. The strong pattern during the

1980s was followed by somewhat weaker but still strong filtering in the 1990s. (For ease of comparison, we retain the sort order of the 1980s.)

The generally weaker rate of apartment construction in the 1990s than the 1980s possibly led to slower filtering in the 1990s[9], a construction hypothesis to be tested statistically in a following section. Subsequently, the early 2000s economic boom produced a return to higher levels of construction, whereas the recovery decade after the recession yielded a reduced volume of new multifamily units.[10]

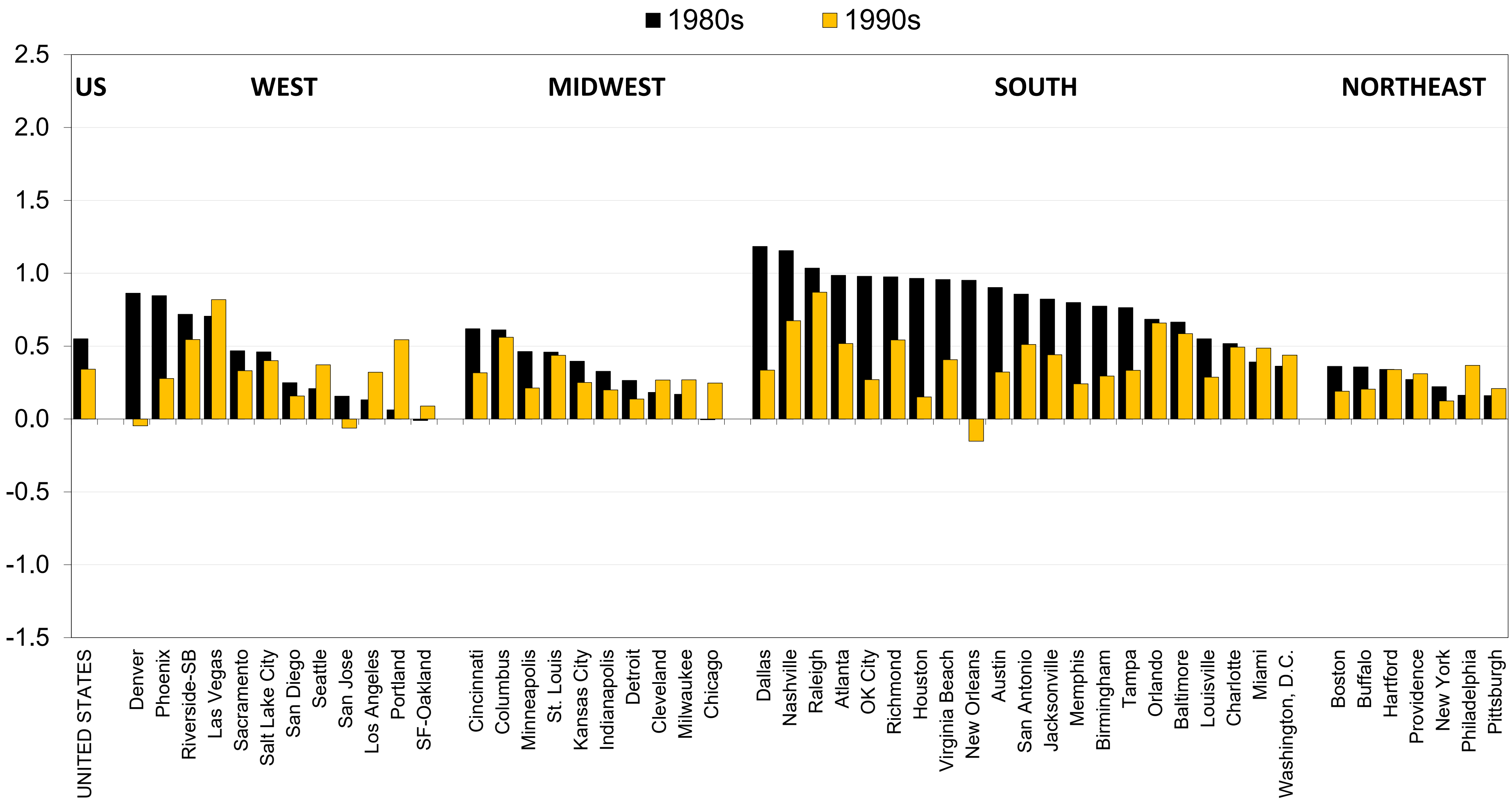
The rate of filtering in apartments rebounded sharply in the early 2000s (Exhibit 9). During the economic boom between 2000 and 2006, apartment units in most large metros increased their occupancy transfer to low-income renters to more than one percent every year, and the national rate of filtering surged to 0.75 percent per year, exceeding even the national average of 0.60 achieved in the 1980s.

This period of robust filtering was cut short by the financial crisis and recession beginning in 2008 and was totally reversed in the years following the Great Recession. The nation and its large metros gave back the previous gains of low-income occupancy in apartment units. Filtering reversal amounted to 0.25 per year for the nation in the 2010s and were even greater in many of the western metros and prominently in Detroit and a few midwestern metros. In the South, Atlanta and Oklahoma City stand out for their strong reversal of filtering after an earlier decade of strong increase. Running against these currents, a small group of the large metros managed to yield increases in filtering despite the negative tide. Overall, the financial crisis and economic bust also led to a bust for filtering.

[9] Annual building permits for multifamily units nationwide ran 567,000 in the 1980s and 312,000 in the 1990s.

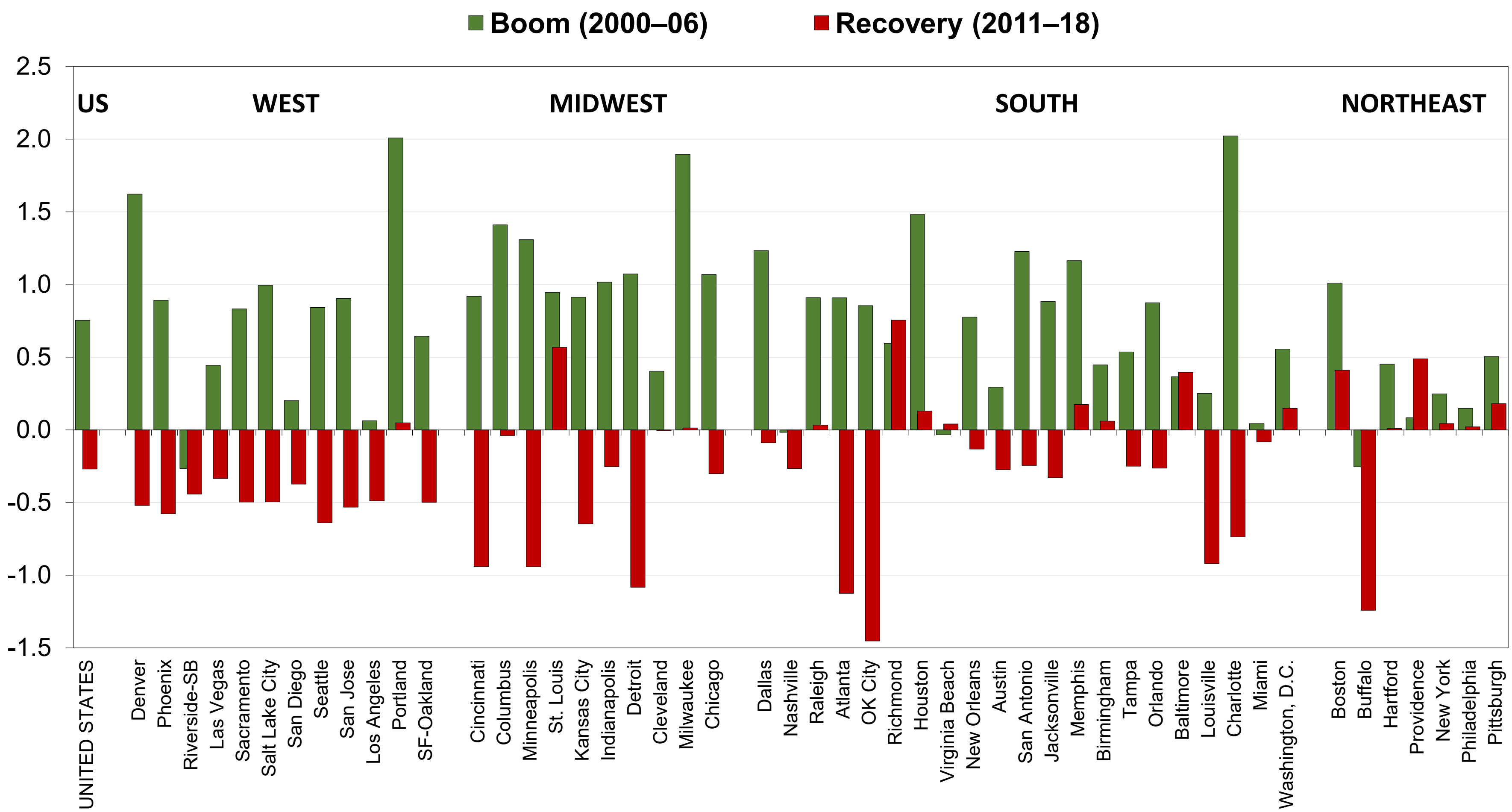
[10] In the early 2000s, multifamily permits amounted to 434,000 per year, well above the 1990s, followed by 338,000 per year from 2007 to 2010. From 2011 to 2018, annual permits were 358,000 per year, not much above recession years and well below early 2000s.

Exhibit 8. Annualized Percentage Point Change in Low-income Share of Apartment Units, 1980s and 1990s
(50 largest metropolitan areas only; excluding construction after the beginning of each decade)



Sources: 1980, 1990 and 2000 Decennial Census; 2006 and 2018 American Community Survey 1-year IPUMS Microdata files (Ruggles et al., 2019).

Exhibit 9. Annualized Percentage Point Change in Low-income Share of Apartment Units, 2000-06 Boom and 2011-18 Recovery (50 largest metropolitan areas only; excluding construction after the beginning of each decade; excluding 2007-10 recession)



Sources: 1980, 1990 and 2000 Decennial Census; 2006 and 2018 American Community Survey 1-year IPUMS Microdata files (Ruggles et al., 2019).

4. ESTIMATION OF METROPOLITAN CONTEXTUAL EFFECTS ON APARTMENT FILTERING

What contextual factors in metropolitan areas could increase or decrease the rate of filtering in apartment housing? Differences between metros and decades were identified in preceding section. A particular question is what can explain the extreme reversal in filtering direction after the Great Recession? Filtering theory has long posited that an adequate supply of new housing is required to free up older housing and allow filtering to operate. In tighter markets with less supply, rents are driven higher and tenants tend to hold tight to their existing units rather than move upward to better housing. For lack of turnover and sufficient vacancies, the opportunities to lower-income renters would be much diminished.

Factors Important to Filtering

The key explanatory factor to test is the relative quantity of new construction: How much housing is added relative to the rate of economic and population growth. It is simply a matter of supply and demand, but how that demand is formed and expressed is a multipronged process.

On the supply side, housing additions are measured by summing building permits[11] in an interval, lagging these two years to account for the time span prior to completion and potential occupancy. We utilize the permits for number of units in multifamily structures.

The demand side is multifaceted, and we have several instruments to tap each facet. One commonly used indicator is the rate of economic growth, which draws migration to metro areas and supports household demand for housing. We will follow the practice of representing economic growth by the rate of job growth in each metro area.

Population growth might also be used to represent growth in total demand, but all people do not wield equal housing demand, and studies in housing demography show that an increase in babies or children is far less consequential for housing demand than growth in some other age groups. In any event, we already propose to use job growth to represent total housing needs.

Instead, more strategic demographic analysis can be used to identify key population segments that drive the growth of demand for rental apartments. Studies show that two thirds of occupants in newly built apartments are households ages 20 to 34 and that the rise or fall of the number of young adults arriving at age 25 measures the pressure for rental household formation (Myers and Pitkin 2009; Myers and Gearin 2001).

A further insight is that the rise and fall of the homeownership rate for young adults creates ebbs and flows in the demand

[11] While it might seem ideal to use data on housing completions, or at least housing starts, the data we have access to at the metropolitan scale for the 100 largest metros is the building permit series collected by the U.S. Census Bureau.

for rental housing. Homeownership rates rose to a peak during the homeownership bubble of the 2000s, skimming middle-income renters into homeowning, mostly in single-family units. Conversely, the ten percentage point decline in homeownership rates beginning after 2006 created an unprecedented surge of "diverted homeowners" that were thrown into the rental market (Myers, Painter, Lee and Park 2012). Thus, metros with greater declines in homeownership may have more congested rental markets where filtering is more impeded.

Data and Model Specification

Our analysis incorporates these explanatory factors in an aggregated metropolitan-level analysis that pools data for housing vintages in the 100 largest metropolitan areas. Observations are made in five time intervals within the span of 1980 to 2018: the 1980s, 1990s, the boom period of 2000 through 2006, the bust period of 2007 through 2011 and the recovery period after 2011. We trace the filtering in apartment units in each of these intervals in relations to the prevailing supply and demand conditions. Thus, the units of observation across the vintages and metro areas amount to 2,300 time segments pooled for statistical analysis.[12] This sample is constructed from observation of rental housing units in multifamily structures with fiveor more units. Individual units are not followed over time; rather, independent samples are drawn from the same vintage in the same metro area, amounting to longitudinal samples constructed from repeated cross-sectional surveys (Myers 1999).

The dependent variable, as discussed in previous sections, is the change in low-income occupancy share between the beginning and end of each time interval. The expectation from filtering theory is that the lower-income share of each vintage will grow ever higher as the units grow older, which occurs for each vintage as time passes. However, the pace of housing construction relative to job growth, as well as other factors, could speed up or slow down the aging-based pace of filtering.

We estimate the net change in low-income (< 50 percent of area median household income (AMI)) occupancy share of apartments (5+ units in structure) in relation to key characteristics of the metropolitan areas in which they are located. The model to be described is associational and cannot test causality.p
The overall model to be estimated can be expressed as:

$$\Delta Y_{ijk} = (Y_{ij,t+10} - Y_{ij,t}) = C_{jk} + J_{jk} + \Delta M_{ijk} + \rho_k + \alpha_i$$

Where ΔY_{ijk} is percentage point change in period k (from t to t + 10) in the low-income share of renters in apartment vintage i in metropolitan area j; C_{jk} is the new construction rate in metropolitan area j in period k as detailed in the following section; J_{jk} is the job-growth rate in metropolitan area j in period k; ΔM_{ijk} is changes in characteristics of metropolitan area j in period k; ρ_k is the period-specific fixed effects in 1980s, 1990s (reference), boom, bust and recovery period; and α_i is the period-invariant differences among apartment vintages, identified by their year-structure-built dummy, in 10-year groups from pre-1960, 1960s (reference), 1970s, 1980s, 1990s and 2000s. All variables were annualized to adjust for the different length of each interval of observation.

An alternative measure of housing supply replaces C_{jk} and J_{jk} in some models with relative housing supply (S_{jk}) in metropolitan area j in period k. This relative housing supply measure is developed according to procedures described in Appendix C.

[12] The pooled sample of 2,300 = (6 vintages × 5 periods × 100 metro areas) less 700 cells of later-period vintages not observable in earlier periods (e.g., 2000s-vintage apartments did not exist during 1980s).

Variables

Definitions of variables used in this analysis are given in Exhibit 10.

Exhibit 10. Definition of Variables

	Variable	Definition
Dependent	Net Change in Low-income Occupancy of Vintage Apartment	Percentage point change during a time interval in low-income (< 50% of AMI) share of an apartment (5+ units in structure) vintage in a metropolitan area
Independent	New Construction	Summed annual building permits during a time interval (2-year lag applied) in a metropolitan area divided by absolute count of base year households multiplied by 100
	Relative Housing Supply	Actual less expected new housing construction during a time interval in a metropolitan area; expected new construction is fitted value of 100-metro regressions between job growth rate and new construction rate
	Job Growth	Growth rate of absolute count of jobs during a time interval in a metropolitan area
	Changes in Age 25-34 Homeownership	Percentage point change in the per capita homeownership rate of age 25 to 34 population during a time interval in a metropolitan area
	Fixed Period Effects	Dummy variables of 5 time intervals including 1980s, 1990s (reference), boom from 2000 through 2006, bust from 2007 through 2011, and recovery from 2012 through 2018
	Fixed Vintage Effects	Dummy variables of 6 apartment vintages including pre-1960, 1960s (reference), 1970s, 1980s, 1990s, and 2000s

Notes: See Appendix C for estimating shortage of new construction relative to job growth. All variables were annualized by the length of years in each time interval.

Results

Period and Vintage Fixed Effects

We first show estimation results that only include period or vintage fixed effects and a constant term (Exhibit 11). These plain fixed effects are background to evaluate the contribution of adding key metropolitan contextual factors in the following models.

Period effect model in Exhibit 11 includes a set of coefficients to represent fixed period effects (expressed relative to a reference period of the 1990s). Compared to the 1990s, 0.190 percentage point greater filtering occurred in the 1980s and 0.317 percentage point greater filtering occurred in the boom period. During the recession period, filtering was weaker and not significant, but in the post-recession recovery period, filtering was strongly significant statistically and twice as negative compared to the 1990s, as the 1980s were positive. These findings correspond to the previous line graph (Exhibit 4 panel b) that showed roughly parallel trends between vintages in an earlier section.

Separately, the vintage effect model in Exhibit 11 includes only vintage fixed effects with a reference group of the 1960s-vintage. Compared to 1960s-vintage, newer vintages underwent significantly weaker filtering, particularly the newest 2000s-vintage had 0.820 percentage point weaker filtering during the recent recovery period (2011 through 2018). Even the oldest vintage (pre-1960) had 0.285 percentage point weaker filtering than 1960s-vintage. That weaker filtering may be because the oldest apartments within the oldest vintage are most likely to be demolished and totally exit from the rental market, or it might also be that the surviving units in this oldest vintage are also more at risk for gentrification.

The overall model R-squares are much stronger in period fixed model (0.090) than vintage fixed model (0.018), implying the greater variation of period effects and their importance to explain filtering. In contrast, the relatively low R-squares of vintage fixed model correspond to the above line graph (Exhibit 4 panel b), which displayed roughly parallel trends between vintages.

Exhibit 11. Pooled Regression Results for Filtering of Apartment Housing, By Fixed Period and Vintage Effects, 100 Largest Metropolitan Areas, 1980 to 2018

	Period Effect Model		Vintage Effect Model	
	Coef.	Sig.	Coef.	Sig.
Fixed Period Effects				
1980–1990	0.190	***		
1990–2000 (Ref.)				
2000–2006	0.317	***		
2006–2011	−0.109			
2011–2018	−0.579	***		
Fixed Vintage Effects				
Pre-1960			−0.279	***
1960s-vintage (Ref.)				
1970s-vintage			−0.131	+
1980s-vintage			−0.177	*
1990s-vintage			−0.176	+
2000s-vintage			−0.767	***
Constant	0.336	***	0.432	***
Number of Obs.	2,300		2,300	
Adj. R-squared	0.090		0.018	

Notes: + = $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Universe is renter-occupied 5+ multifamily housing units in each of the 100 largest metropolitan areas. Low-income is defined as earning half or less of metro area median household income in each year. Robust standard errors were used to account for heteroskedasticity.

Metropolitan Characteristics

Exhibit 12 shows regression estimation results that incorporate key characteristics of metropolitan areas. Panel (a) of Exhibit 12 focuses on the effects of new construction and job growth on filtering, while panel (b) replaces those two supply and demand-side variables with our estimate of relative housing supply as discussed above and in Appendix C. Overall, we find a consistent and significant positive effect of new construction on filtering.

Model 1 of Panel (a) includes new construction and job growth as explanatory variables. New construction has a very significant positive effect on filtering, while job growth also has a significant negative effect on filtering. Later, in models reported in Panel (b), we introduce an alternative measure of *relative housing supply* that combines the effects of job and housing growth.

Model 2 introduces the additional variable of change in homeownership rate among people ages 25-34. This variable measures percentage point change in a given time interval, also annualized. The result shows that a one percentage point increase (decrease) in the age 25-34 homeownership rate is associated with a 0.521 percentage point increase (decrease) in low-income occupancy of apartment units. This finding spotlights the interconnection between rental and owner markets. Specifically, this implies that an increase in the homeownership rate among young adults eases rental competition and opens greater opportunities for low-income renters. Instead, after the Great Recession, homeownership fell ten percentage points for young adults, and filtering was reduced proportionally.

Exhibit 12. Pooled Regression Results for Filtering of Apartment Housing, 100 Largest Metropolitan Areas, 1980 to 2018

(a) Effects of New Construction and Job Growth										
	Model (1)		Model (2)		Model (3, Base)		Model (4)		Model (5)	
	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
New Construction	1.775	***	2.139	***	1.511	***	2.044	***	1.511	***
Job Growth	−0.570	***	−1.059	***	−0.814	***	−1.005	***	−0.814	***
Changes in Age 25-34 Homeownership			0.521	***	0.443	***	0.513	***	0.443	***
Fixed Period Effects										
1980–1990					0.367	***			0.371	***
1990–2000 (Ref.)										
2000–2006					0.120	*			0.110	+
2006–2011					−0.048				−0.058	
2011–2018					−0.321	***			−0.312	***
Fixed Vintage Effects										
Pre-1960							−0.279	***	−0.279	***
1960s-vintage (Ref.)										
1970s-vintage							−0.131	*	−0.131	*
1980s-vintage							−0.211	**	−0.119	
1990s-vintage							−0.202	*	−0.086	
2000s-vintage							−0.504	***	−0.234	+
Constant	−0.009		0.163	***	0.246	***	0.344	***	0.378	***
Number of Obs.	2,300		2,300		2,300		2,300		2,300	
Adj. R-squared	0.046		0.081		0.113		0.091		0.119	

Notes: + = $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Universe is renter-occupied 5+ multifamily housing units in each of the 100 largest metropolitan areas. Low-income is defined as earning half or less of metro area median household income in each year. Robust standard errors were used to account for heteroskedasticity.

Exhibit 12 Continued

(b) Effect of Relative Housing Supply										
	Model (1)		Model (2)		Model (3, Base)		Model (4)		Model (5)	
	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
Relative Housing Supply	0.215	***	0.221	***	0.223	***	0.221	***	0.223	***
Changes in Age 25-34 Homeownership			0.289	***	0.407	***	0.296	***	0.407	***
Fixed Period Effects										
1980–1990					0.400	***			0.404	***
1990–2000 (Ref.)										
2000–2006					0.297	***			0.288	***
2006–2011					0.255	*			0.246	+
2011–2018					−0.462	***			−0.453	***
Fixed Vintage Effects										
Pre-1960							−0.279	***	−0.279	***
1960s-vintage (Ref.)										
1970s-vintage							−0.131	+	−0.131	*
1980s-vintage							−0.190	**	−0.119	+
1990s-vintage							−0.161	+	−0.086	
2000s-vintage							−0.779	***	−0.234	+
Constant	0.255	***	0.339	***	0.322	***	0.519	***	0.455	***
Number of Obs.	2,300		2,300		2,300		2,300		2,300	
Adj. R-squared	0.014		0.026		0.112		0.045		0.118	

Notes: + = $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Universe is renter-occupied 5+ multifamily housing units in each of the 100 largest metropolitan areas. Low-income is defined as earning half or less of metro area median household income in each year. Robust standard errors were used to account for heteroskedasticity.

Model 3 is our preferred model and introduces a set of coefficients to represent fixed period effects (expressed relative to a reference period of the 1990s). Compared to the 1990s, 0.367 percentage point greater filtering occurred in the 1980s and 0.120 percentage point greater filtering occurred in the boom period. During the recession period, filtering was weaker and not significant, but in the post-recession recovery period, filtering was strongly significant statistically and twice as negative compared to the 1990s, as the 1980s were positive. This model can be compared to the period fixed effect model of Exhibit 11 above. The negative filtering effect in the post-recession period was reduced from −0.579 to −0.321 once the effects of housing and employment growth were added along with the decrease in homeownership. What may be surprising is that half of this negative period effect persists even after control for these other variables.

Model 4 includes vintage fixed effects with a reference group of the 1960s-vintage. Compared to 1960s-vintage, newer vintages underwent significantly weaker filtering; particularly, the newest 2000s-vintage had 0.504 percentage point weaker filtering during the recent recovery period (2011 to 2018). Even the oldest vintage (pre-1960) had 0.279 percentage point weaker filtering than 1960s-vintage. That weaker filtering may be because the oldest apartments within the oldest vintage are most likely to be demolished and totally exit from the rental market, or it might also be that the surviving units in this oldest vintage are also more at risk for gentrification.[13]

Model 5 incorporates both period and vintage dummy variables, and it largely confirms results from models 3 and 4, particularly, very similar with model 3.

Models in panel (b) are identical to those just discussed, save that we substitute a measure of relative supply instead of separate measures of construction and job growth. The alternative supply measure is strongly significant, and the overall model R-squares remain very similar to those in models of panel (a). Behavior of other model factors is altered to a moderate degree. The coefficient on homeownership change is moderately reduced, while the fixed period effects are strengthened considerably. In model 4, when the fixed vintage effects are added, the overall model fit falls to only half that of model 4 when employment and construction are entered separately.

Overall, findings in panel (b) are consistent with those in panel (a). Base model 3 includes our shortage measure and homeownership of age 25-34 as explanatory variables, both of which are very significant and have coefficients of 0.223 and 0.407, respectively. This means that one percentage point greater new construction than expected based on job growth is related with 0.223 percentage point additional increase in the low-income share among the apartment tenants. The coefficient for the age 25-34 homeownership rate (0.407) also supports the strong interconnections between homeowner market and low-income rental opportunities, as we found in panel (a).

Additional Tests

We conducted additional tests to see how stable the effects are across time periods of key variables that influence the increase in low-income occupancy, our measure of apartment filtering. Exhibit 13 reports tests by adding interactions between selected key variables and period fixed effects to our base model (model 3). We find that the estimates for none of the key variable effects varied significantly by period, save for one, the change in homeownership rate at age 25-34, and that was in the single period of the 2000 to 2006 boom. Homeownership increases among young adults during the boom period had an additional positive effect (0.615) on the increase in low-income occupancy of apartment housing.

The other interactions between period dummies and new construction (or relative housing supply or job growth) are not statistically significant, implying that construction effects are relatively consistent across different periods. The homeownership interaction also may be of questionable significance, because even though the interaction is significant for one period (2000 to 2006), the direct homeownership coefficient is sharply reduced and rendered insignificant as the interactions absorb the relation between homeownership changes and filtering.

[13] Previous filtering studies, including Rosenthal (2014), also report the pace of filtering slows as housing units age over time (and possibly even reverses in very old ages).

Exhibit 13. Pooled Regression Results with Interaction Terms Between Key Variable and Period Fixed-Effects Added to Base Model 3

Key Variable of Interest:	New Construction		Relative Housing Supply		Job Growth		Changes in Age 25-34 Homeownership	
	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
New Construction	1.883	***			1.448	***		
Relative Housing Supply			0.263	***			0.223	***
Job Growth	−0.878	***			−0.810	*		
Changes in Age 25-34 Homeownership	0.456	***	0.390	***	0.478	***	0.169	
Interaction Between Key Variable								
× 1980–1990	−0.140		−0.055		0.047		−0.130	
× 1990–2000 (Ref.)								
× 2000–2006	0.201		0.024		0.349		0.615	*
× 2006–2011	−0.793		−0.040		−0.255		0.235	
× 2011–2018	−0.953		−0.184		−0.036		0.154	
Fixed Period Effects								
1980–1990	0.387	***	0.392	***	0.376	***	0.215	*
1990–2000 (Ref.)								
2000–2006	0.021		0.298	***	0.050		0.257	***
2006–2011	0.130		0.240	+	−0.007		0.244	
2011–2018	−0.176		−0.467	***	−0.303	*	−0.491	***
Constant	0.195	**	0.323	***	0.255	***	0.330	***
Number of Obs.	2,300		2,300		2,300		2,300	
Adj. R-squared	0.114		0.112		0.113		0.112	

Notes: + = $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Universe is renter-occupied 5+ multifamily housing units in each of the 100 largest metropolitan areas. Low-income is defined as earning half or less of metro area median household income in each year. Robust standard errors were used to account for heteroskedasticity.

5. COMPARISONS TO SUPPLY OF SUBSIDIZED HOUSING

How much does all this filtering add to the total low-income housing opportunity provided in apartment housing? If filtering occurs at a small annual rate of roughly half a percent a year, that could generate a sizable number of units when multiplied against an existing stock that is approaching 20 million rental apartments.

We seek a measure of the relative importance of filtering, placing this in perspective by weighing the volume of housing provided through the filtering process against the number of government subsidized low-income housing units added in the same time period. The comparison is important for helping planners and policy makers decide how much of the low-income housing needs can be met by *naturally occurring affordable housing (NOAH)* and how much might require additional housing assistance programs (HUD, 2016).

In this section, we produce a national comparison between the volume of added units by these different means, focusing on changes since 2000 because of the better quality data contained in two HUD databases since that time. We compare filtered market units and federally subsidized units in three sub-periods—economic boom of 2000 to 2006, downturn of 2006 to 2011 and the post-recession recovery years of 2011 to 2018.

Method to Estimate the Count of Federally Subsidized Rental Apartment Units

The federal government operates a number of housing assistance programs to help lower-income Americans afford rentals (HUD, 2017a; Schwartz, 2015). We estimate the number of federally subsidized rental housing units in the nation as a whole by combining American Community Survey (ACS) microdata, HUD's annual Picture of Subsidized Households database and HUD's Low-Income Housing Tax Credit (LIHTC) database.[14] HUD's Picture of Subsidized Households database provides nationally aggregated data, while the ACS microdata and LIHTC database provide individual housing units or LIHTC development project-level data.

We combine these sources to estimate federally subsidized units that match the selection used in our filtering analysis—rental apartments in five or more unit structures that have become home to low-income renters (household incomes below 50 percent of the area median). To match the different sources together requires some assumptions, because some data sources do not distinguish structure type, and some do not separate subsidized units from nonsubsidized. Our goal is to estimate the annual growth in low-income renter-occupied apartment units so that we can compare filtered and federally subsidized alternatives.

[14] Other existing national estimates (Harvard JCHS, 2020; HUD, 2017a; Schwartz, 2015; Weicher et al., 2017, 2018) roughly match our ACS-based estimates.

Our total sample is ACS-defined housing units occupied by renter households with low income (<50 percent of national median household income). These are distributed across the following categories:

(a) Filtered market-rate apartment units
(b) Filtered market-rate single-family units and units in 2-4 unit structures
(c) Subsidized apartment units
(d) Subsidized single-family units and units in 2-4 unit structures

Estimation of each case count is inferred from a sequence of steps in six different hierarchical dimensions recorded in the ACS data and HUD's databases.

First, only occupied units are considered, because low-income occupancy is how we measure low-income opportunity. This means vacant units are excluded in our estimates. ACS microdata allows us to identify occupied units versus vacant units, while HUD's Picture of Subsidized Households database has two distinct variables named Subsidized Units Available and percent Occupied, which allows simple multiplication to calculate a new variable of Occupied Subsidized Units. However, HUD's LIHTC database does not provide information on occupied status of individual units in each LIHTC development project, which leads us to count all LIHTC units regardless of occupied status and consequently overestimate slightly the LIHTC benefits.

Second, only renter-occupied units are counted. ACS microdata allows us to identify renter-occupied units versus owner-occupied units, while HUD's databases, both Picture of Subsidized Households and LIHTC, are basically only about renters, and thus no adjustment is needed to HUD's databases.

Third, only low-income-occupied units are considered. ACS microdata allows us to identify dollar amount of individual tenant income, calculating <50 percent of median, while HUD's Picture of Subsidized Households database has a variable named *percent Very Low Income (i.e., <50 percent of median)*, which allows additional multiplication to the step-1 generated variable of Occupied Subsidized Units. This results in a new variable of Low-income Occupied Subsidized Units. A different procedure of this step is required by HUD's LIHTC database, which provides two different variables named *Total Units* and *Low-income Units* for each LIHTC development project. (On average, 96 percent is designated for low-income households as described on page 145 of Schwartz 2015.) However, the income eligibility for LIHTC is 60 percent or below of area median household income, which is higher than the general income restriction (50 percent or below of AMI) of other federal subsidies. Schwartz (2015, p.145) explains that residents of LIHTC developments tend to have higher incomes than their counterparts in Public Housing and other federal rental subsidy programs, and approximately 21 percent of the LIHTC residents have incomes above 50 percent of AMI, and the remaining 79 percent is below 50 percent of AMI. Since HUD's LIHTC database does not offer any variables about income of LIHTC tenants, we take the percentage estimate (79 percent) and multiply it by the above-mentioned *Low-income Units* variable. This multiplication excludes the portion of *Low-income Units* that is in the range of 50-60 percent of AMI, resulting in a new estimated variable of Low-income (<50 percent of AMI) Units.

Fourth, we distinguish housing units into either 5-or-more unit multifamily structures or 4-or-less unit multifamily structures because 5+ apartment structures are of our interest. ACS microdata allow us to identify the number of units in each structure. Although virtuall all (99.5 percent) of LIHTC units are in 5+ unit apartment structures, HUD's Picture of Subsidized Households database does not provide any information on structure type.

To distinguish the apartments, we rely on HUD's national report titled "Characteristics of HUD-Assisted Renters and Their Units in 2013," which provides a national summary table on the "Distribution of HUD-Assisted Housing by Structure Type, 2013." (See details in Table 6-1 on page 27 of HUD 2017a.) It reports that 55.3 percent of HUD-assisted rental housing units are in 5+ unit apartment structures. The apartment share is particularly low in the case of the voucher program, only 29.3 percent, compared to its counterparts in Public Housing apartment units (50.1 percent) and Other HUD-Subsidized apartment units (80.9 percent). These three percentages (29.3 percent for Voucher, 50.1 percent for Public Housing and 80.9 percent for Other HUD-Subsidized) are taken and multiplied by our estimates drawn from HUD's Picture of Subsidized Households in order to estimate subsidized apartment units in fiveor more unit structures.

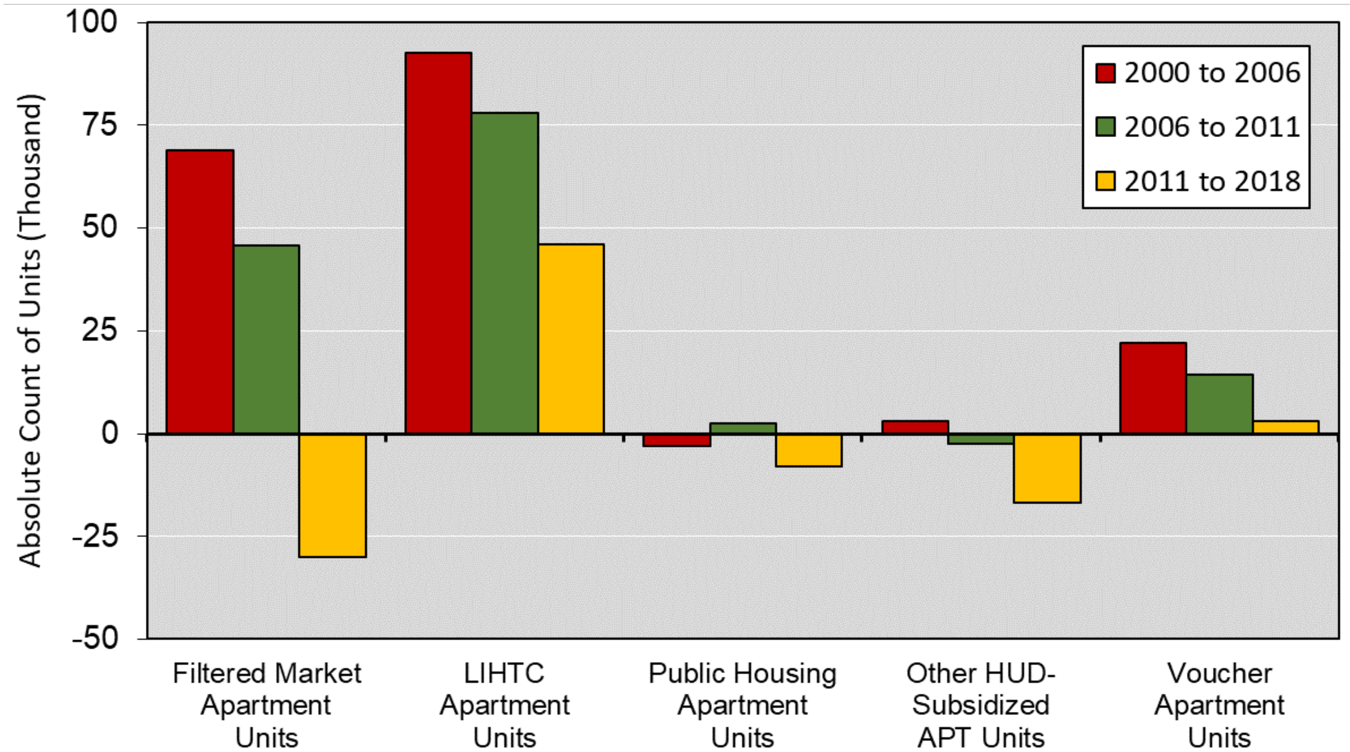
Fifth, HUD's Picture of Subsidized Households and LIHTC databases cover nine kinds of major federal programs: LIHTC, Housing Choice Vouchers, Public Housing, Mod Rehab, Project-Based Section 8, RentSup/RAP, S236/BMIR, 202/PRAC and 811/PRAC. However, those databases do not include other subsidy programs, such as Indian Housing, HOME Investment Partnership, Community Development Block Grants (CDBG) and those of the U.S. Department of Agriculture's Rural Housing Service. State and local programs are also excluded.

Finally, it should be noted that our estimates constructed from the HUD databases likely overstate the total number of subsidized housing units due to "double counting" of units that draw upon multiple programs. This impacts estimates for individual programs like LIHTC, voucher and all the other kinds of programs included in this analysis. For example, illustrating overlap of LIHTC and voucher, LIHTC housing often accommodates low-income households with vouchers, and 7 to 13 percent of all voucher holders reside in LIHTC units (Schwartz, 2015, p.145). The result of this program double counting is that the volume of the federally assisted housing opportunity is somewhat overstated, possibly as much as 10 percent, and as a result, *our conclusions about the relative importance of filtering versus federally subsidized programs may be somewhat understated.*

National Comparisons of Filtered Units and New Supply of Subsidized Housing

Our resulting estimates of growth in low income-occupied units are compared in three different periods, including periods of boom (2000 to 2006), bust (2006 to 2011) and recovery (2011 to 2018) (Exhibit 14). We present the trends in five panels, corresponding to units added by (1) growth in low-income opportunity through filtering of market-rate housing, (2) growth of the LIHTC tax-based program, (3) growth in Public Housing, (4) growth in other HUD-subsidized programs and (5) growth in voucher-holding households. All of these are estimated specifically for the portions of programs in rental apartment units in structures with fiveor more units and restricted to low-income tenants.

Exhibit 14. Annualized Change in Number of Filtered Market Rate Apartment Units and Federally Subsidized Apartment Units, United States, 2000 to 2006, 2006 to 2011 and 2011 to 2018



Notes: The filtered market units in each period are exclusive of construction after the period begins. LIHTC apartment units include units placed in service in 2000 and later. Other HUD-Subsidized Apartment Units include federal programs such as Mod Rehab, Project-Based Section 8, RentSup/RAP, S236/BMIR, 202/PRAC and 811/PRAC. All estimates pertain to low-income renters (<50 percent of median).
Sources: HUD's Picture of Subsidized Households database, 2019; HUD's LIHTC database, 2019; 2000 Decennial Census IPUMS; 2006, 2011 and 2018 ACS 1-year IPUMS

It bears attention that the voucher program in panel (5) is different from the others. The first four panels measure increases in supply of housing occupied by low-income renters. In contrast to these supply-side programs, the voucher program assists the income of renters but does not create new occupancy opportunities. The unfortunate reality is that low-income renters are extremely burdened by the rent requirements they face. In every vintage of apartment, the great majority of low-income tenants, more than 70 percent, are paying more than 30 percent of income on housing (see Appendix D). This problem existed in 1980 and it has only increased in recent years (Myers and Park 2019, Exhibit 1 on page 167; Harvard JCHS 2020, Figure 4 on page 4). The voucher program essentially buys down the rent of a tenant to a level equal to only 30 percent of their income. The voucher program is so small and the waiting lists so long that gaining access to this rent subsidy is considered like winning a lottery. It is regrettable that so few low-income renters ever achieve this benefit.

Affordability is a serious problem, but a more recent harm has increasingly threatened. The severity of the housing shortages following the financial crisis in 2008 has meant that sizable numbers of would-be renters are prevented from finding a home at any price. It is low-income renters, especially the young, who are most likely to be denied housing and dislodged. While it is ideal to pay rent that is below 30 percent of income, a first order of business is to find suitable living units to accommodate every low-income household. Expanded opportunities of housing supply are more keenly needed than ever before.

New low-income opportunities produced by filtering are presented in panel (1) of Exhibit 14. The vintage longitudinal trends presented in Section 1 showed that filtering remained strong in the boom period, resembling that of earlier decades, but thereafter it subsided. These results are represented in Exhibit 14. Fully 69,000 additional filtered apartment units were added every year between 2000 and 2006, as was indicated by the growing share in low-income occupancy. The filtering momentum weakened in the bust period, adding 46,000 filtered units per year from 2006 to 2011. However, after 2011, the filtering process reversed in the recovery period and lost 30,000 previously filtered units annually. Note that this result matches our previous findings as shown by vintage longitudinal trendlines in Exhibit 4 and columns in Exhibit 9.

A somewhat larger flow of opportunity than filtering was provided through the LIHTC tax-based program. In fact, the LIHTC program expanded more rapidly in recent years than any others in providing subsidized housing for low-income renters (Harvard JCHS 2020, Figure 33). Roughly 92,000 LIHTC apartment units were added per year in the early-2000s boom period. The pace slowed in the following bust and recovery periods but remained a stronger source of new supply than both filtering and all other subsidized units (Exhibit 14, panel 2).

Both filtering and the LIHTC program dwarf the new opportunity produced by all of the HUD-sponsored programs, including Public Housing and others. Other supply-side subsidized apartment units, both Public Housing and Other HUD-Subsidized, increased very moderately in either boom or bust periods and even notably declined by 8,000 and 17,000 units per year in the recent recovery years. The demand-side voucher program showed the most growth of all the HUD-sponsored programs, adding 22,000 units per year deployed in apartments during the boom period but slowing thereafter to near zero growth.

Without filtering of market-rate housing in 2000 to 2006, new low-income housing opportunity would have been a good 40 percent less than what was otherwise available. In the past several years, the filtering contribution has been lost, even reversed, and total opportunity has shrunk to barely one-quarter of before.

CONCLUSION

This study has focused on long-term impacts of filtering in rental apartments, measured by the degree to which the aging of apartments is associated with greater occupancy by low-income renters. We found a major change in impacts before and after the Great Recession. The nation's acute housing crisis of recent years is founded on a shortage of housing that drives up rents, worsens affordability problems and even spurs a rise in homelessness (Harvard JCHS 2020). What this report shows, in the context of the shortage, is that the long-assumed filtering process for providing low-income housing has ceased to operate and is even running in reverse, shifting housing away from low-income occupancy.

Filtering can no longer be taken for granted as a "naturally occurring" source of affordable housing. For one thing, the shortage crisis has caused all housing to be unaffordable, consuming a larger share of occupants' incomes—even in the middle class—than deemed acceptable. Filtered units still are not affordable, but they are shelter, which is especially valued in a shortage. However, the downward filtering of housing opportunity can no longer be viewed as a permanent fact of nature. In decades past it was the substantial flow of new construction, largely targeted to middle- and higher-income groups, that enabled the filtering process to operate. In the face of its current constriction, well below levels normally associated with employment growth, we gain fresh appreciation for the broader benefits of housing construction.

The housing stock requires nurturing if we wish to avoid losses of low-income opportunity as well as a surge in homelessness. Direct expenditures for subsidized housing may be a required solution, and substantial increases certainly are warranted in proportion to the burgeoning problems. Yet tenant subsidies have never been sufficiently supplied for all those in need in the United States, and now the needs are so much greater than before. In the face of always-limited public resources, policy makers should reexamine the filtering process as a crucial solution for expanding low-income access to housing.

The present study provides evidence of how much the effectiveness of filtering is increased when overall housing construction is greater. It also supplies evidence of the surprising effect of homeownership decline on the filtering of rental apartments. The collapse of homeownership rates after 2006 shifted eight million more households into rental competition (Myers et al., 2016), blocking the downward filtering of apartments and even pulling them upward. Thus, we see how low-income access to housing depends on trends that impact the middle class as well. In the end, we are reminded that the housing market is an integrated web of substitutions serving a diversity of people, all of whom are struggling for shelter, and none of whom can be neglected without consequences for the others.

REFERENCES

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

Joint Center for Housing Studies of Harvard University. (2019). The State of the Nation's Housing. Cambridge, MA: Joint Center for Housing Studies of Harvard University.

Joint Center for Housing Studies of Harvard University. (2020). America's Rental Housing. Cambridge, MA: Joint Center for Housing Studies of Harvard University.

Myers, D. (1999). Cohort Longitudinal Estimation of Housing Careers, Housing Studies, 14, 473-90.

Myers, D., & Gearin, E. (2001). Current Preferences and Future Demand for Denser Residential Environments. Housing Policy Debate, 12(4), 633–659.

Myers, D., & Mawhorter, S. L. (2012). Filtering. In A. T. Carswell (Ed.), The Encyclopedia of Housing. Thousand Oaks, CA: SAGE Publications.

Myers, D., Painter, G., Lee, H., & Park, J. (2016). Diverted Homeowners, the Rental Crisis and Foregone Household Formation. Washington, D.C.: Research Institute for Housing America (RIHA).

Myers, D., & Park, J. (2019). A Constant Quartile Mismatch Indicator of Changing Rental Affordability in U.S. Metropolitan Areas, 2000 to 2016. Cityscape: A Journal of Policy Development and Research, 21(1), 163–200.

Myers, D., & Pitkin, J. (2009). Demographic Forces and Turning Points in the American City, 1950-2040. The ANNALS of the American Academy of Political and Social Science, 626(1), 91–111.

Ratcliff, R. U. (1949). Urban Land Economics. New York: McGraw-Hill.

Rosenthal, S. S. (2014). Are Private Markets and Filtering a Viable Source of Low-Income Housing? Estimates from a "Repeat Income" Model. American Economic Review, 104(2), 687–706.

Ruggles, S., Flood, S., Goeken, R., Grover, J., Meyer, E., Pacas, J., & Sobek, M. (2019). IPUMS USA: Version 9.0 [dataset]. Minneapolis, MN: IPUMS.

Schwartz, A. F. (2015). Housing Policy in the United States (3rd ed.). New York, NY: Routledge.

Somerville, T. C., & Holmes, C. (2001). Dynamics of the Affordable Housing Stock: Microdata Analysis of Filtering. Journal of Housing Research, 12(1), 115–140.

U.S. Department of Housing and Urban Development. (2016). Research Symposium on Gentrification and Neighborhood Change. Washington, D.C.: U.S. Department of Housing and Urban Development.

U.S. Department of Housing and Urban Development. (2017a). Characteristics of HUD-Assisted Renters and Their Units in 2013. Washington, D.C.: U.S. Department of Housing and Urban Development.

U.S. Department of Housing and Urban Development. (2017b). Worst Case Housing Needs: 2017 Report to Congress.

Washington, D.C.: U.S. Department of Housing and Urban Development.

U.S. Department of Housing and Urban Development. (2018). Understanding Whom the LIHTC Serves. Washington, D.C.: U.S. Department of Housing and Urban Development.

U.S. Department of Housing and Urban Development. (2019a). Low-Income Housing Tax Credit (LIHTC) Database. Washington, D.C.: U.S. Department of Housing and Urban Development.

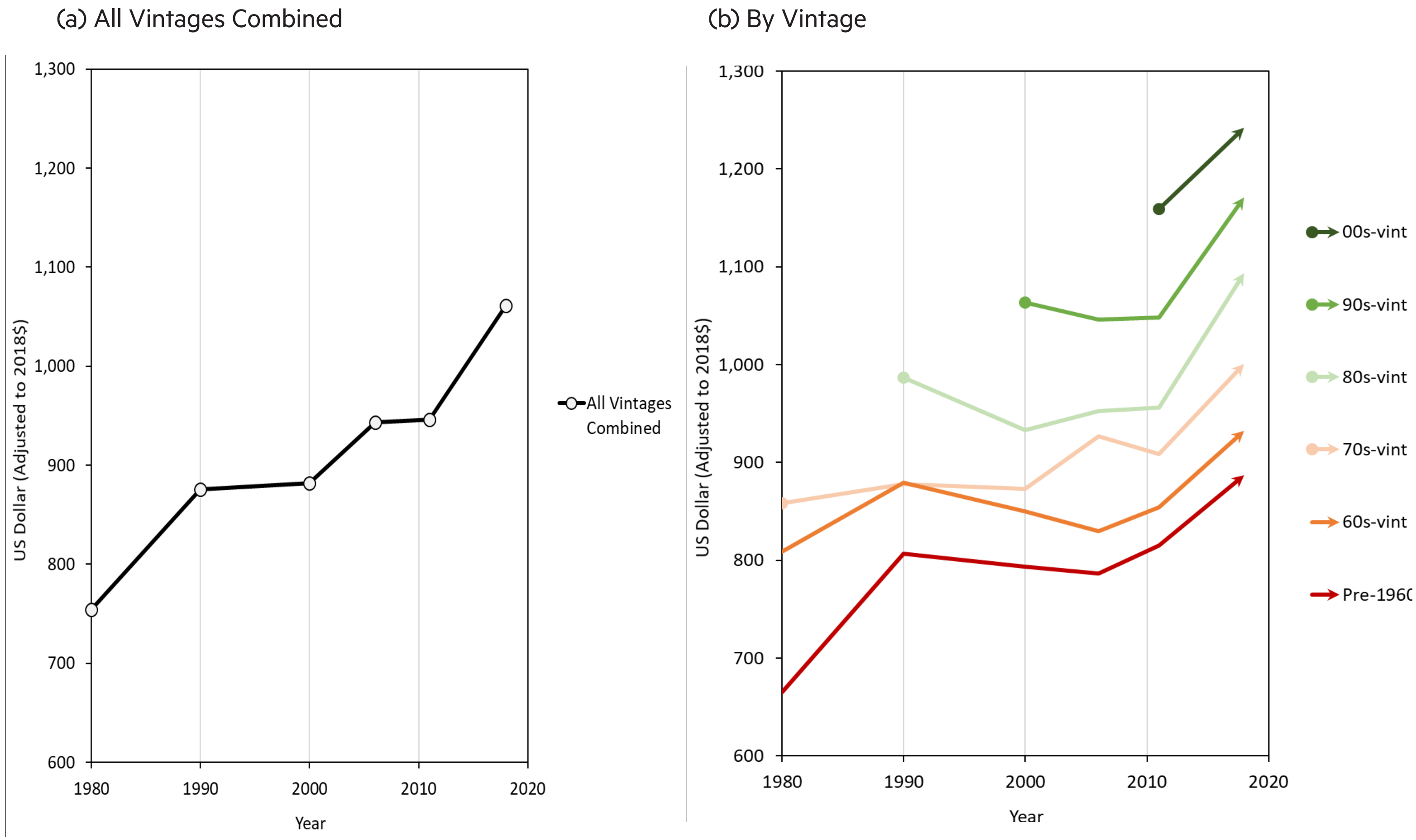
U.S. Department of Housing and Urban Development. (2019b). Picture of Subsidized Households Database. Washington, D.C.: U.S. Department of Housing and Urban Development.

Weicher, J. C., Eggers, F. J., & Moumen, F. (2017). The Long-Term Dynamics of Affordable Rental Housing. Hudson Institute.

Weicher, J. C., Eggers, F. J., & Moumen, F. (2018). The Long-Term Dynamics of Affordable Rental Housing: Creating and Using a New Database. Cityscape: A Journal of Policy Development and Research, 20(2), 235–244.

APPENDIX

Appendix A. Vintage Longitudinal Trend in Gross Rent of Apartment Housing, 100 Largest Metropolitan Areas, 1980 to 2018



Notes: Universe is renter-occupied housing units in structures with fiveor more units in each metro area. All dollar values were inflation-adjusted to 2018$. Gross rent includes contract rent and utilities. Low-income households are defined as earning half or less of their metropolitan median household income in each survey year. Trend lines are the average of 100 largest metro areas, weighted by absolute count of households in each metro area and survey year.
Sources: 1980, 1990 and 2000 Decennial Census; 2006, 2011 and 2018 American Community Survey 1-year IPUMS Microdata files (Ruggles et al., 2019).

Appendix B. Low-Income Occupancy and Gross Rent of Apartment Housing Units, By Vintage of Structure, Three Selected Metropolitan Areas, 1980 to 2018

Metropolitan Area Name	Vintage of Structure	Low-income (<50% of AMI) Share of Apartment Housing Units						Median Gross Rent (Inflation Adjusted to 2018$) of Apartment Housing Units					
		1980	1990	2000	2006	2011	2018	1980	1990	2000	2006	2011	2018
Los Angeles	Pre-1960	46.3	43.4	46.3	44.9	48.6	46.7	726	1,024	916	1,107	1,170	1,367
	1960s	33.5	36.2	40.1	39.9	43.1	39.1	863	1,110	1,003	1,194	1,215	1,382
	1970s	30.7	35.0	36.8	37.9	36.8	35.4	991	1,152	1,058	1,302	1,270	1,473
	1980s		34.3	37.2	38.4	39.3	35.7		1,344	1,131	1,275	1,298	1,538
	1990s			40.2	41.0	46.1	38.1			1,125	1,278	1,323	1,516
	2000s					40.7	38.1					1,389	1,594
	All Vintages Combined	37.8	37.7	40.5	41.1	42.6	39.0	850	1,159	1,057	1,271	1,260	1,509
Washington, D.C.	Pre-1960	45.6	46.8	49.2	54.2	52.7	50.4	717	1,000	897	949	995	1,159
	1960s	30.3	35.8	42.2	43.7	47.4	50.0	865	1,104	976	1,016	1,140	1,258
	1970s	32.1	40.6	45.0	47.4	47.2	51.1	922	1,071	1,004	1,184	1,183	1,293
	1980s		36.2	40.7	44.0	46.1	43.4		1,268	1,120	1,236	1,304	1,378
	1990s			33.7	42.3	33.4	40.7			1,247	1,312	1,486	1,404
	2000s					31.4	35.1					1,624	1,650
	All Vintages Combined	36.2	40.4	43.1	45.9	43.8	43.9	840	1,119	1,071	1,241	1,352	1,481
SF-Oakland	Pre-1960	47.9	44.5	45.1	47.6	47.3	46.8	735	1,074	1,136	1,050	1,127	1,480
	1960s	35.1	37.2	39.7	43.5	46.8	37.5	876	1,166	1,217	1,198	1,239	1,693
	1970s	35.1	39.2	38.6	42.1	40.0	39.0	922	1,165	1,275	1,296	1,304	1,671
	1980s		36.3	37.2	44.0	40.0	35.6		1,323	1,417	1,373	1,498	1,877
	1990s			36.2	47.4	46.2	47.7			1,463	1,389	1,450	1,788
	2000s					43.6	45.1					1,462	1,793
	All Vintages Combined	40.7	40.4	40.8	45.0	44.3	41.8	846	1,191	1,278	1,291	1,341	1,779

Notes: All dollar values were inflation-adjusted to 2018$. Universe is renter-occupied 5+ multifamily housing units in each metro area. SF-Oakland is San Francisco-Oakland metro area. AMI is metropolitan area median household income. The category of All Vintages Combined includes post-2010 vintage in 2011 and 2018 data.
Sources: 1980, 1990 and 2000 Decennial Census; 2006, 2011 and 2018 ACS IPUMS Microdata files.

Appendix C. Estimating Shortage of New Construction Relative to Job Growth

Housing production in the United States in recent years has been running lower than normally expected in comparison to job growth. This has spurred close examination of what is the “normal” relationship, and it has led to development of a measure of relative supply that is based on comparison of actual construction versus jobs-based expectations.

Estimating the Jobs-Housing Relationship

The solution adopted here is to estimate the jobs-housing growth relationship separately within each time period, comparing the rate of housing growth[15] to job growth[16] for a sample of the 100 largest metropolitan areas. The housing construction relationship to employment growth is simply described as:

$HC = a + bE$,

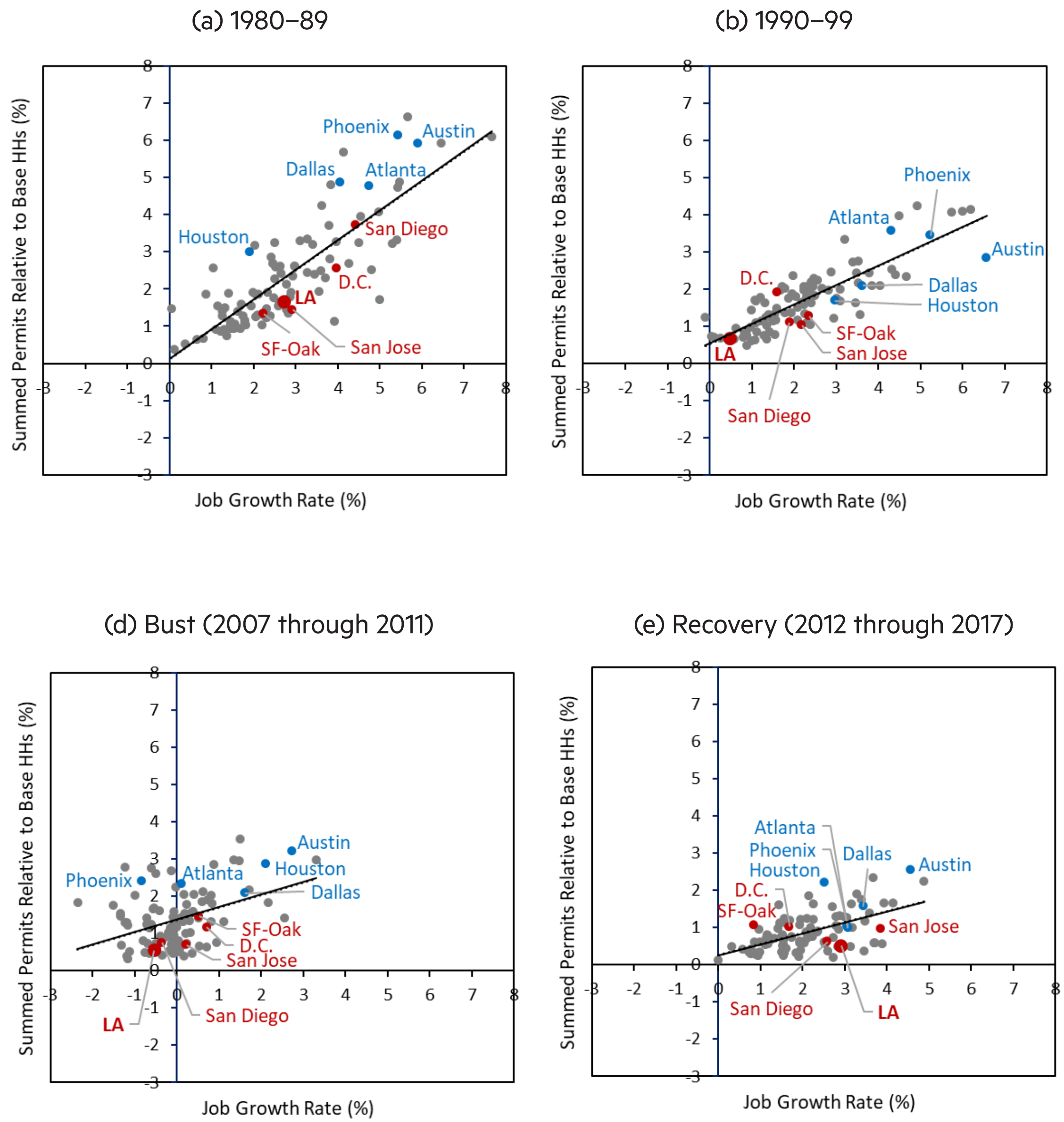
where HC is housing construction (annual percent); E is employment growth (annual percent); *b* is a parameter to be estimated; and a is a constant term also to be estimated. This constant term, or intercept, can be interpreted in this case as reflecting the general willingness to support housing construction regardless of amount of employment growth.

The rates of housing and employment growth for each of the 100 largest metros are displayed in Appendix Exhibit C-1, segmented by five discrete periods covering 1980-89, 1990-99, boom period of 2000 through 2006, bust period of 2007 through 2011 and recovery years of 2012 through 2017. All five plots are drawn to the same dimensions, so a visual inspection reveals real differences between eras. In the 1980s, the higher construction and employment growth for the 100 metros is clearly apparent, as is the severe contraction in the bust period of 2007 to 2011. Especially surprising is how weak the housing and economic growth is in the recovery years after 2011. The expected rate of construction in each metro is derived from each period’s rate of employment growth, and the trend line summarizes that relation for each period.

[15] New construction in each locale is represented by annual building permits, lagged two years and cumulated for the number of years in the period. The new construction rate is an annual percentage constructed by dividing this cumulated sum of permits by the base year number of occupied housing units (households), multiplied by 100, and dividing by the number of years in the length of the period. We assume a two-year time lag between permit authorization of a housing unit and actual occupancy of that unit.

[16] Employment growth in each locale is derived as the difference in total employment between beginning and ending year of the period. The employment growth rate is an annual percentage constructed by dividing this difference by the number of jobs at the beginning of the period, multiplied by 100, and dividing by the number of years in the length of the period.

Appendix Exhibit C-1. Relations Between Annualized Job Growth and New Construction, 100 Largest Metropolitan Areas



Notes: Job growth and new construction rates were annualized for comparison across periods of different lengths. X- and Y-axis are in the same scale across periods. Single dot represents a metropolitan area. Selected metro areas were labeled and highlighted red (California metros and D.C., which are often under the trend line across periods) or blue (Texas metros, Phoenix and Atlanta, which are often above the trend line across periods).

Sources: U.S. Bureau of Economic Analysis (BEA)'s Employment Data; U.S. Census Bureau's Building Permits Survey; 1980, 1990 and 2000 Decennial Census IPUMS; 2006, 2011 and 2017 ACS 1-year IPUMS.

In most periods, housing permits for new construction in the LA metro lie well short of what is expected by the regression trend line that equates permits to job growth. Other California metro areas and Washington, D.C., (highlighted red) are also located below the trend line, while Phoenix, Atlanta and Texas metro areas are often above the trend line (highlighted blue). Los Angeles appears to lie closest to the trend line of jobs-based expectations in the 1990s and falls furthest short of expectations in the recent recovery period.

The relationship of housing to employment growth appears to evolve over the decades, as reflected in the changing parameters summarized in Appendix Exhibit C-2. One key parameter changing across the periods is the "slope" coefficient describing the overall relationship of new construction to job growth in the 100 metros. In the recovery period, the annual percentage rate of construction increased by 0.29 for every 1.0 percent of employment growth. This is barely half of the coefficient value that prevailed in periods before the 2007 crisis.

A second key parameter is the constant term (intercept) in each time period, which varies from a low of 0.12 in the 1980s to more than 1.00 in both the 2000s boom and bust, before falling back to 0.25 in 2012 to 2017. The high intercept in the boom period (aka the bubble) is consistent with excessive construction of that era, while the even higher intercept during the bust is likely a product of overspill from the boom era of construction already in the pipeline and also the continuation of housing growth even while employment turned negative. In contrast, the very low intercept in the recovery period after 2012 reflects greater discouragement of housing production no matter the housing demand. Thus, what makes construction especially anemic in the recovery years is the combination of both a very weak coefficient on employment growth and a very minimal intercept (0.25).

Appendix Exhibit C-2. Summary of Relations Between Job Growth and New Construction Across 100 Largest Metropolitan Areas and Los Angeles' Experience

	Relations Across 100 Metros			Los Angeles Metro Area			
	(a) Coefficient on Job Growth	**(b)** Constant Term	**(c)** R-squared	**(d)** LA Actual % Job Growth	**(e)** LA Actual % Housing Growth	**(f = a × d + b)** LA EXPECTED Value for % Housing Growth	**(g = e – f)** LA Deviation of Actual from Expected
1980–89	0.80	0.12	0.68	2.73	1.66	2.30	–0.64
1990–99	0.52	0.53	0.71	0.49	0.66	0.79	–0.12
Boom (2000 Through 2006)	0.59	1.08	0.56	0.97	0.69	1.65	–0.96
Bust (2007 Through 2011)	0.34	1.37	0.17	–0.54	0.55	1.19	–0.64
Recovery (2012 Through 2017)	0.29	0.25	0.34	2.91	0.51	1.11	–0.60
Average of 80s, 90s, and Boom	0.64	0.58		1.40	1.01	1.47	–0.46

Notes: Job growth and construction rates were annualized for comparison across periods of different lengths.
Sources: U.S. Bureau of Economic Analysis (BEA)'s Employment Data; U.S. Census Bureau's Building Permits Survey; 1980, 1990 and 2000 Decennial Census IPUMS; 2006, 2011 and 2017 ACS 1-year IPUMS.

When the five plots of Exhibit C-1 are compared overall, the cluster of metro data points, as well as the trend line linking permits to jobs, fall much lower in the recovery period than in the previous periods. Taking the Los Angeles metro as a good example for explanation, the fact that LA falls well below the trend line in the recovery era indicates LA's shortfall relative to an already depressed standard. Were LA's housing construction to be elevated to the average level of the recovery period, that would only partially represent the existing housing shortage. A more complete measure of unmet needs in the LA metro, and in other metros, can be derived by applying the more normal relationships observed in the period before the financial crisis in 2007. For this purpose, we can make use of the average of regression relationships across the three earlier periods (1980 to 2006). These average coefficients are shown in the bottom row of Exhibit C-2.

The degree of shortage estimated in each metro in the recovery era is found by first generating the expected housing growth under the pre-crisis conditions (multiplying the actual employment growth rate for the metro by the averaged coefficient of housing growth and also summing the average constant term). When this expected growth is compared to the actual rate of housing growth, the shortage is estimated simply as:

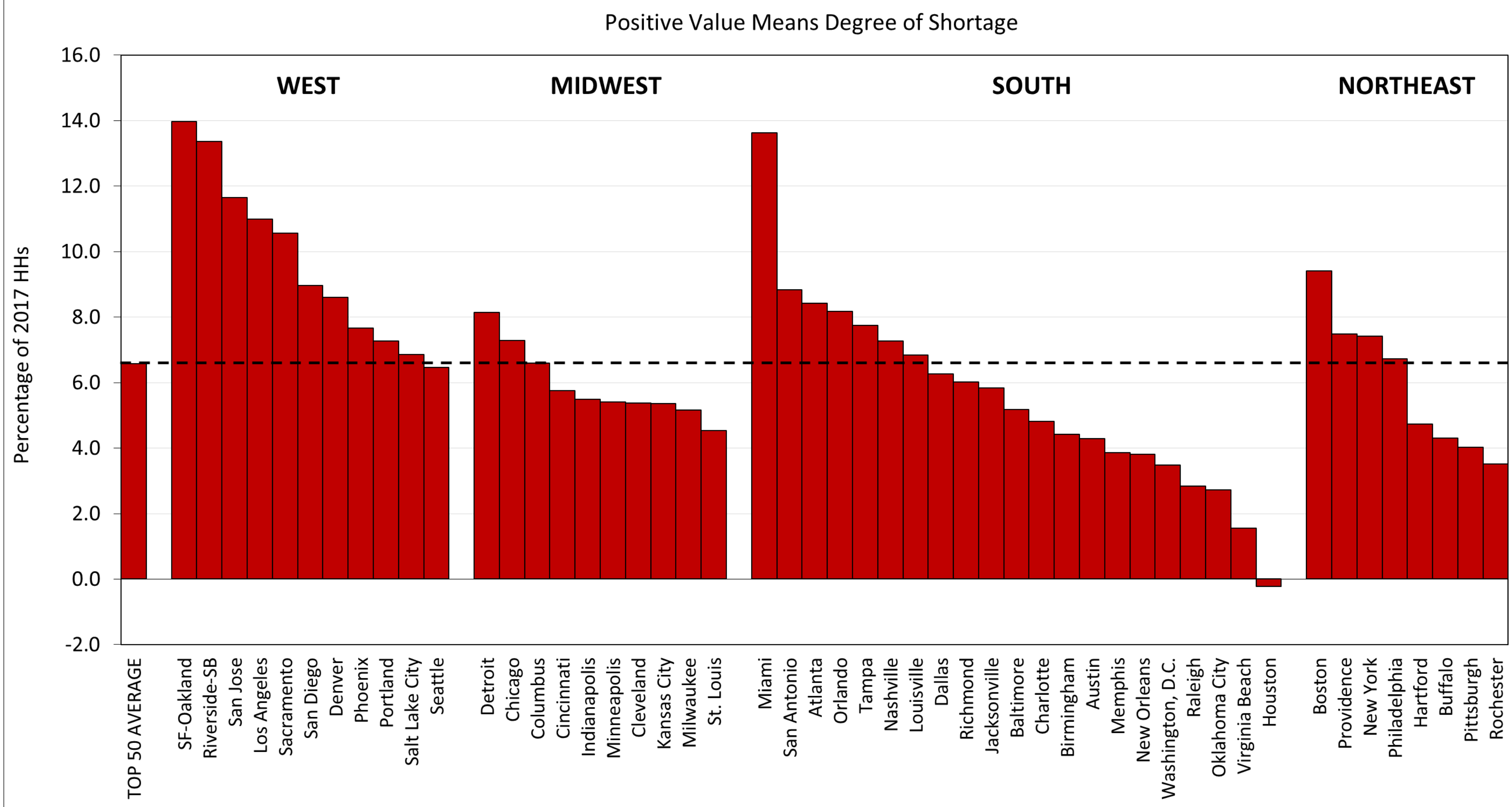
Housing shortage = Actual housing growth – Expected housing growth

Calculating Housing Shortage in Large Metropolitan Areas

We lastly compare the shortfall estimated for the 50 largest metro areas in the United States (see Appendix Exhibit C-3).[17] Only six metros exceed ten percent shortfall in housing growth relative to their employment growth in the recovery period: Miami in the south region, and five California metros in the west. On this measure, the Los Angeles metro is the fourth worst in the nation; however, in light of its much larger size than the others, the percentage shortfall equates to a larger absolute number of unmet housing needs, approximating a half million shortage accrued since 2012.

[17] For these comparisons, shortfall estimates are prepared of the total number of housing units and are expressed as a % of the end-of-period housing stock in 2017. That permits an easier comparison of unmet needs.

Appendix Exhibit C-3. Degree of Housing Shortage Relative to Job Growth, 50 Largest Metropolitan Areas, 2012 through 2017



Notes: Based on Normal Relationships between Job Growth and Permits from 1980 to 2006. Dashed horizontal line means the average degree (6.6 percent) of housing shortage across the largest 50 metro areas. SF-Oakland means San Francisco-Oakland metro area, while Riverside-SB is Riverside-San Bernardino metro area. HHs is households.
Sources: U.S. Bureau of Economic Analysis (BEA)'s Employment Data; U.S. Census Bureau's Building Permits Survey; 1980, 1990 and 2000 Decennial Census IPUMS; 2006, 2011 and 2017 ACS 1-year IPUMS.

Appendix D. Prevalence of Excess Rent Burden Among Low-Income Apartment Renters:
Share of Each Vintage Paying More Than 30 Percent of Income on Rent, 100 Largest Metropolitan Areas, 1980 to 2018

	(a) Rent-burdened Share (%) of Apartment Vintages					
	1980	1990	2000	2006	2011	2018
Pre-1960 Vintage	76.7	76.9	76.3	81.7	84.4	84.1
1960s Vintage	80.5	79.5	74.5	80.4	83.5	81.1
1970s Vintage	71.4	73.6	77.1	81.3	83.9	82.2
1980s Vintage		74.4	73.9	78.7	82.1	81.7
1990s Vintage			72.6	78.3	80.5	82.5
2000s Vintage					84.9	86.0
All Vintages Combined	73.4	74.0	73.7	79.7	82.5	81.8

	(b) Difference from Previous Observation Year				
	1980–1990	1990–2000	2000–2006	2006–2011	2011–2018
Pre-1960 Vintage	0.3 ***	–0.6 ***	5.4 ***	2.7 ***	–0.3 +
1960s Vintage	–1.1	–4.9 **	5.8 **	3.1	–2.4
1970s Vintage	2.2 *	3.5	4.2 ***	2.6	–1.7
1980s Vintage		–0.5	4.8 ***	3.4	–0.3 ***
1990s Vintage			5.6 ***	2.2	2.1
2000s Vintage					1.1
All Vintages Combined	0.7 **	–0.3	6.0 ***	2.9 ***	–0.8

Notes: + = $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Universe is renter-occupied 5+ multifamily housing units in each of the 100 largest metropolitan areas. A household is defined rent burdened when paying more than 30 percent of household income on gross rent. The category of All Vintages Combined includes post-2010 vintage in 2011 and 2018 data.
Sources: 1980, 1990 and 2000 Decennial Census; 2006, 2011 and 2018 ACS IPUMS Microdata files.

Appendix E. List of 100 Metropolitan Areas and Constituent Counties

Rank by 2010 Pop	Simplified Metropolitan Area Name	Number of Counties	Constituent Counties
1	New York	23	Bergen, Bronx, Essex, Hudson, Hunterdon, Kings, Middlesex, Monmouth, Morris, Nassau, New York, Ocean, Passaic, Pike, Putnam, Queens, Richmond, Rockland, Somerset, Suffolk, Sussex, Union, Westchester
2	Los Angeles	2	Los Angeles, Orange
3	Chicago	13	Cook, DeKalb, DuPage, Grundy, Jasper, Kane, Kendall, Kenosha, Lake, McHenry, Newton, Porter, Will
4	Dallas	12	Collin, Dallas, Delta, Denton, Ellis, Hunt, Johnson, Kaufman, Parker, Rockwall, Tarrant, Wise
5	Houston	10	Austin, Brazoria, Chambers, Fort Bend, Galveston, Harris, Liberty, Montgomery, San Jacinto, Waller
6	Philadelphia	11	Bucks, Burlington, Camden, Cecil, Chester, Delaware, Gloucester, Montgomery, New Castle, Philadelphia, Salem
7	Washington, D.C.	22	Alexandria city, Arlington, Calvert, Charles, Clarke, District of Columbia, Fairfax city, Fairfax, Falls Church city, Fauquier, Frederick, Fredericksburg city, Jefferson, Loudoun, Manassas city, Manassas Park city, Montgomery, Prince George's, Prince William, Spotsylvania, Stafford, Warren
8	Miami	3	Broward, Miami-Dade, Palm Beach
9	Atlanta	28	Barrow, Bartow, Butts, Carroll, Cherokee, Clayton, Cobb, Coweta, Dawson, DeKalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Haralson, Heard, Henry, Jasper, Lamar, Meriwether, Newton, Paulding, Pickens, Pike, Rockdale, Spalding, Walton
10	Boston	7	Essex, Middlesex, Norfolk, Plymouth, Rockingham, Strafford, Suffolk
11	SF-Oakland	5	Alameda, Contra Costa, Marin, San Francisco, San Mateo
12	Detroit	6	Lapeer, Livingston, Macomb, Oakland, St. Clair, Wayne
13	Riverside-SB	2	Riverside, San Bernardino
14	Phoenix	2	Maricopa, Pinal
15	Seattle	3	King, Pierce, Snohomish
16	Minneapolis	13	Anoka, Carver, Chisago, Dakota, Hennepin, Isanti, Pierce, Ramsey, Scott, Sherburne, St. Croix, Washington, Wright
17	San Diego	1	San Diego
18	St. Louis	16	Bond, Calhoun, Clinton, Franklin, Jefferson, Jersey, Lincoln, Macoupin, Madison, Monroe, St. Charles, St. Clair, St. Louis city, St. Louis, Warren, Washington
19	Tampa	4	Hernando, Hillsborough, Pasco, Pinellas
20	Baltimore	7	Anne Arundel, Baltimore city, Baltimore, Carroll, Harford, Howard, Queen Anne's
21	Denver	10	Adams, Arapahoe, Broomfield, Clear Creek, Denver, Douglas, Elbert, Gilpin, Jefferson, Park
22	Pittsburgh	7	Allegheny, Armstrong, Beaver, Butler, Fayette, Washington, Westmoreland

23	Portland	7	Clackamas, Clark, Columbia, Multnomah, Skamania, Washington, Yamhill
24	San Antonio	8	Atascosa, Bandera, Bexar, Comal, Guadalupe, Kendall, Medina, Wilson
25	Sacramento	4	El Dorado, Placer, Sacramento, Yolo
26	Orlando	4	Lake, Orange, Osceola, Seminole
27	Cincinnati	15	Boone, Bracken, Brown, Butler, Campbell, Clermont, Dearborn, Franklin, Gallatin, Grant, Hamilton, Kenton, Ohio, Pendleton, Warren
28	Cleveland	5	Cuyahoga, Geauga, Lake, Lorain, Medina
29	Kansas City	15	Bates, Caldwell, Cass, Clay, Clinton, Franklin, Jackson, Johnson, Lafayette, Leavenworth, Linn, Miami, Platte, Ray, Wyandotte
30	San Jose	2	San Benito, Santa Clara
31	Columbus	8	Delaware, Fairfield, Franklin, Licking, Madison, Morrow, Pickaway, Union
32	Charlotte	6	Anson, Cabarrus, Gaston, Mecklenburg, Union, York
33	Indianapolis	10	Boone, Brown, Hamilton, Hancock, Hendricks, Johnson, Marion, Morgan, Putnam, Shelby
34	Austin	5	Bastrop, Caldwell, Hays, Travis, Williamson
35	Virginia Beach	16	Chesapeake city, Currituck, Gloucester, Hampton city, Isle of Wight, James City, Mathews, Newport News city, Norfolk city, Poquoson city, Portsmouth city, Suffolk city, Surry, Virginia Beach city, Williamsburg city, York
36	Providence	5	Bristol, Kent, Newport, Providence, Washington
37	Nashville	13	Cannon, Cheatham, Davidson, Dickson, Hickman, Macon, Robertson, Rutherford, Smith, Sumner, Trousdale, Williamson, Wilson
38	Milwaukee	4	Milwaukee, Ozaukee, Washington, Waukesha
39	Jacksonville	5	Baker, Clay, Duval, Nassau, St. Johns
40	Memphis	8	Crittenden, DeSoto, Fayette, Marshall, Shelby, Tate, Tipton, Tunica
41	Louisville	13	Bullitt, Clark, Floyd, Harrison, Henry, Jefferson, Meade, Nelson, Oldham, Shelby, Spencer, Trimble, Washington
42	Richmond	20	Amelia, Caroline, Charles City, Chesterfield, Colonial Heights city, Cumberland, Dinwiddie, Goochland, Hanover, Henrico, Hopewell city, King and Queen, King William, Louisa, New Kent, Petersburg city, Powhatan, Prince George, Richmond city, Sussex
43	OK City	7	Canadian, Cleveland, Grady, Lincoln, Logan, McClain, Oklahoma
44	Hartford	3	Hartford, Middlesex, Tolland
45	New Orleans	7	Jefferson Parish, Orleans Parish, Plaquemines Parish, St. Bernard Parish, St. Charles Parish, St. John the Baptist Parish, St. Tammany Parish
46	Raleigh	3	Franklin, Johnston, Wake
47	Buffalo	2	Erie, Niagara
48	Salt Lake City	3	Salt Lake, Summit, Tooele
49	Birmingham	7	Bibb, Blount, Chilton, Jefferson, Shelby, St. Clair, Walker
50	Rochester	5	Livingston, Monroe, Ontario, Orleans, Wayne
51	Tucson	1	Pima
52	Honolulu	1	Honolulu
53	Tulsa	7	Creek, Okmulgee, Osage, Pawnee, Rogers, Tulsa, Wagoner
54	Fresno	1	Fresno
55	Bridgeport	1	Fairfield

56	Albuquerque	4	Bernalillo, Sandoval, Torrance, Valencia
57	Albany	5	Albany, Rensselaer, Saratoga, Schenectady, Schoharie
58	Omaha	8	Cass, Douglas, Harrison, Mills, Pottawattamie, Sarpy, Saunders, Washington
59	New Haven	1	New Haven
60	Bakersfield	1	Kern
61	Dayton	4	Greene, Miami, Montgomery, Preble
62	Oxnard-TO	1	Ventura
63	Allentown	4	Carbon, Lehigh, Northampton, Warren
64	Baton Rouge	9	Ascension Parish, East Baton Rouge Parish, East Feliciana Parish, Iberville Parish, Livingston Parish, Pointe Coupee Parish, St. Helena Parish, West Baton Rouge Parish, West Feliciana Parish
65	El Paso	1	El Paso
66	Worcester	1	Worcester
67	McAllen	1	Hidalgo
68	Grand Rapids	4	Barry, Ionia, Kent, Newaygo
69	Columbia	6	Calhoun, Fairfield, Kershaw, Lexington, Richland, Saluda
70	Greensboro	3	Guilford, Randolph, Rockingham
71	North Port	2	Manatee, Sarasota
72	Akron	2	Portage, Summit
73	Little Rock	6	Faulkner, Grant, Lonoke, Perry, Pulaski, Saline
74	Knoxville	5	Anderson, Blount, Knox, Loudon, Union
75	Springfield	3	Franklin, Hampden, Hampshire
76	Stockton	1	San Joaquin
77	Charleston	3	Berkeley, Charleston, Dorchester
78	Syracuse	3	Madison, Onondaga, Oswego
79	Toledo	4	Fulton, Lucas, Ottawa, Wood
80	CO-Springs	2	El Paso, Teller
81	Greenville	3	Greenville, Laurens, Pickens
82	Wichita	4	Butler, Harvey, Sedgwick, Sumner
83	Boise City	5	Ada, Boise, Canyon, Gem, Owyhee
84	Lakeland	1	Polk
85	Des Moines	5	Dallas, Guthrie, Madison, Polk, Warren
86	Madison	3	Columbia, Dane, Iowa
87	Youngstown	3	Mahoning, Mercer, Trumbull
88	Augusta	6	Aiken, Burke, Columbia, Edgefield, McDuffie, Richmond
89	Ogden	3	Davis, Morgan, Weber
90	Harrisburg	3	Cumberland, Dauphin, Perry
91	Palm Bay	1	Brevard
92	Jackson	5	Copiah, Hinds, Madison, Rankin, Simpson
93	Chattanooga	6	Catoosa, Dade, Hamilton, Marion, Sequatchie, Walker
94	Provo	2	Juab, Utah
95	Lancaster	1	Lancaster
96	Modesto	1	Stanislaus

97	PortlandME	3	Cumberland, Sagadahoc, York
98	Durham	4	Chatham, Durham, Orange, Person
99	Deltona	1	Volusia
100	Santa Rosa	1	Sonoma

Source: U.S. Office of Management and Budget (OMB)'s December 2009 delineation files.