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Are Private Markets and Filtering a Viable Source of Low-Income Housing? Estimates from a "Repeat Income" Model†

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While filtering has long been considered the primary mechanism by which markets supply low-income housing, direct estimates of that process have been absent. This has contributed to doubts about the viability of markets and to misplaced policy. I fill this gap by estimating a "repeat income" model using 1985–2011 panel data. Real annual filtering rates are faster for rental housing (2.5 percent) than owner-occupied (0.5 percent), vary inversely with the income elasticity of demand and house price inflation, and are sensitive to tenure transitions as homes age. For most locations, filtering is robust which lends support for housing voucher programs. (*JEL* R21, R31, R38)

Debate about how best to provide housing assistance for low-income families has persisted for decades. Should government emphasize person-based voucher programs that rely on private market supplies of housing, or instead subsidize construction of low-income units as with the Low Income Housing Tax Credit (LIHTC) program (e.g., Eriksen and Rosenthal 2010)? In the background of this debate has been doubt about the ability of private markets to supply low-income housing. It has long been recognized, for example, that developers build little unsubsidized housing for the poor (e.g., Baer 1986). Instead, private markets are thought to provide low-income housing primarily through a dynamic process in which homes built for higher income families slowly deteriorate and filter down to lower income households (e.g., Sweeney 1974; Ohls 1975; Braid 1984; Weicher and Thibodeau 1988; Arnott and Braid 1997). The viability of this process, however, has been questioned. In part, that is because hedonic studies typically yield house rent depreciation rates at or below 0.5 percent per year (e.g., Margolis 1982; Coulson and Bond 1990), a result that is reconfirmed here. Extrapolating, with a 0.5 percent depreciation rate, a 50-year-old home would rent for 78 percent of a newly built home, too high

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seemingly for filtering to be a viable source of low-income housing, and especially so given that rental housing is the traditional home of lower-income families.[1]

This article makes several contributions that clarify whether and under what conditions filtering is an effective long term source of lower-income housing. I develop a new econometric methodology that provides the first-ever direct estimates of the rate at which homes filter down. Based on a simple model of housing demand, I also show that filtering rates are amplified at a nonlinear rate as the income elasticity of demand for housing falls below one. The model structure also indicates that filtering rates vary inversely with the real rate of house rent (price) inflation, and therefore differ across locations.

The core empirical approach is motivated by repeat sales methods first developed by Bailey, Muth, and Nourse (1963) and refined and popularized by Case and Shiller (1989).[2] As is well appreciated, in repeat sales models homes are followed over time and sale prices are compared across sale dates. This differences away time invariant attributes of the individual homes and allows for estimation of an index of "quality adjusted" house price inflation across calendar dates.[3] I modify this approach by comparing the income of newly arrived house occupants across turnover dates. In addition, time is measured not in calendar units but instead by the age of the home as of the date that the home turns over.

Based on this procedure, I estimate a set of indexes using the 1985–2011 American Housing Survey (AHS) panel which follows housing units—not households—over time. The indexes measure the percentage difference in income of arriving occupants across turnover dates as the home ages holding time-invariant house and local attributes constant. Findings indicate that downward filtering is rapid in the first 40 years of a home's life, slows thereafter, and is much faster for rental versus owner-occupied units (roughly 2.5 percent real per year versus 0.5 percent). While I show that depreciation can account for much of the observed filtering in the owner-occupied sector, this is not true for rental housing. The real income of a newly arrived occupant at a 50-year-old rental unit would be just 30 percent of arriving occupant income in a newly built home, far less than the modest depreciation in rents noted above.

Model based estimates resolve this puzzle. Previous studies typically find that the income elasticity of demand for housing is well below one (e.g., Rosen 1979; Hoyt and Rosenthal 1990; Rosenthal, Duca, and Gabriel 1991; Glaeser, Kahn, and Rappaport 2008; and Carrillo, Early, and Olsen 2012). That result is reconfirmed here using the same AHS data as above: for renter and owner-occupied units the estimated income elasticities are 0.124 and 0.413, respectively. I show that these estimates are low enough to substantially amplify the rate at which housing filters down.

An extension highlights that tenure transitions (own versus rent) also affect the rate at which aggregate housing stocks filter down. Three-quarters of recently

[1] Margolis (1982) and Coulson and Bond (1990) both estimate that house rent depreciates at or below 0.5 percent per year and conclude that the filtering is not a viable source of low-income housing for that reason. Chinloy (1979), Smith (2004), and Wilhelmsson (2008) also obtain low rates of rental housing depreciation.

[2] See also Case and Quigley (1991) and Harding, Rosenthal, and Sirmans (2007) for extensions of the repeat sales model.

[3] Harding, Rosenthal, and Sirmans (2007) emphasize that because repeat sales methods do not typically control for age-related depreciation and home maintenance they may over- or understate quality adjusted house price inflation.

built homes are owner-occupied while just two-thirds of the total housing stock is owner-occupied. These values are a reminder that most housing is owner-occupied and that homes tend to shift with age towards the rental sector. Allowing for tenure transitions, the nation's housing stock filters down at a real annual rate of 1.9 percent per year, notably faster than would occur if homes did not tend to shift with age towards the rental sector.

The paper concludes by highlighting that regional differences in house price inflation contribute to differences in filtering rates. This is done by simulating filtering rates using the model described above and 1975–2011 measures of house price appreciation from the Federal Housing Finance Agency (FHFA) house price indexes. For the Northeast and the West, where house price inflation has been highest, housing stocks filter down roughly one-half percentage point slower than for the rest of the country.

Overall, this article confirms that filtering is an important long-run source of lower income housing and also helps to explain why. This lends support for housing voucher-type programs that rely on private market supplies of affordable housing. Findings also indicate that filtering rates vary inversely with house price inflation. The case for subsidized construction of rental housing is, therefore, stronger in cities and regions where house price appreciation tends to be high and filtering is less viable.[4]

To clarify these and other results, Section I describes the data and summary statistics, portions of which provide direct confirmation of filtering. Section II presents standard hedonic regressions and related estimates of house rent (price) depreciation. The repeat income model is developed in Section III along with related results. Section IV extends the model to allow for the influence of housing demand and housing tenure transitions. Section V presents model-based simulations, while Section VI concludes.

I. Data and Summary Statistics

Data for the analysis are taken from the national core files of the 1985–2011 waves of the American Housing Survey (AHS) panel.[5] Each survey contains an extensive array of questions about the house, neighborhood, and occupants. The survey is designed to be approximately representative of the United States and yields a panel that is unique among major surveys in that it follows homes not people. The survey is conducted every odd year (e.g., 1985, 1987, …) and collects data from occupants of roughly 55,000 homes. The exact number of units surveyed varies across years because of budgetary and other considerations (see the Codebook for the AHS, April 2011 for details). As would be expected, few

[4] In contrast, the Low Income Housing Tax Credit (LIHTC) program—the largest Federal subsidized housing construction program in the United States—allocates tax credits across states based solely on the relative size of a state's population (e.g., Eriksen and Rosenthal 2010, Eriksen 2009). Eriksen and Rosenthal (2010) also show that within-state reallocation of credits tends to favor the most populous areas. Such allocation schemes fail to recognize that filtering is likely robust in areas subject to sharply falling real house prices as in the Rust Belt. See Glaeser and Gyourko (2005), Donvan (2009), and Snyder (2010), for related discussion.

[5] Few papers have taken advantage of the panel feature of the AHS, possibly because of the extensive coding efforts required. Recent exceptions include Harding, Rosenthal, and Sirmans (2003, 2007) and Ferreira, Gyourko, and Tracy (2010).

homes are present throughout the entire panel. Instead, individual homes enter and leave the survey at different times, but not in a manner that is likely to bias estimates of filtering rates.[6]

The panel structure of the AHS allows me to observe when a home turns over in the sense that a new set of occupants take up residency in the unit. The data also identify whether a home is currently renter-occupied or owner-occupied and also whether a home changes tenure from rent to own or own to rent upon turning over.[7] These features make it feasible to estimate separate repeat income models for rental units (based on rent-to-rent turnovers), owner-occupied units (based on own-to-own turnovers), and also pooled models that allow for tenure transitions. Other features of the AHS facilitate estimation of hedonic regressions of house rent (price) and housing demand. These latter models provide additional context that highlights links between filtering rates, depreciation, and housing demand.

Several restrictions limit the set of observations included in the estimating sample. First, a common sample was used to estimate the hedonic, housing demand, and filtering models. This helps to ensure that cross-equation linkages that affect filtering rates are not driven by differences in sample composition. All observations included in the sample must therefore include values for all of the variables in the different models. Second, all homes used to estimate the repeat income model must turn over at least twice during the panel so that arriving occupant incomes can be observed. Moreover, when homes first enter the AHS panel, income of the existing occupant at the time that family moved into the home is not observed unless the home was newly constructed. For these reasons, most homes included in the sample appear in at least three different surveys (the initial survey and at least two observed turnovers). Third, after the cuts above, roughly 2.5 percent of families remaining in the sample report zero or negative income.[8] This complicates estimation of the housing demand model which depends on log income. To address this issue, I exclude turnover pairs for which the income of the *first* arriving occupant in a given turnover pair is nonpositive. The housing demand and hedonic regressions are then estimated using only observations on the first-arriving occupant from each turnover pair (e.g., income, rent, socioeconomic attributes).[9] Estimates are quite robust to these sample restrictions.[10]

[6]The AHS is designed and implemented by the Department for Housing and Urban Development (HUD). Conversations with HUD officials confirmed that the composition of the AHS sample is adjusted over time to help ensure that it remains roughly representative of the United States. For a succinct comparison of the sample design and coverage of the American Housing Survey (AHS), the American Community Survey (ACS), and the Current Population Survey (CPS) see http://www.census.gov/housing/homeownershipfactsheet.html. Additional details of the AHS sample design are provided in the codebook manuals listed in the reference section of this article.

[7]The AHS reports whether the current occupant owns or rents the home. In addition, house rent is reported only for rental units, while purchase price, maintenance, and mortgage variables are only reported for owner-occupied units. These variables ensure a reliable classification of housing tenure.

[8]This occurs in other major surveys as well, as with the American Community Survey (ACS).

[9]For turnover pairs for which the second arriving occupant income is nonpositive the dependent variable in the filtering model was set to the percentage change in income across turnover dates instead of the log ratio (as in expression (2)).

[10]The primary exception is that if the income floor was set higher, at say $5,000, the estimated income elasticities of demand for housing increase from 12 to 22 percent for rental units and 41 to 54 percent for owner-occupied homes. In contrast, the various sample restrictions had almost no effect on estimates of the hedonic model depreciation rates. The same was largely true for the filtering model provided that the income floor was based on the *first* as opposed to *second* arriving occupant income in a given turnover pair. As an example, note that in Table 3 (column 3) the estimate of the rate at which rental units filter down based on the sample described above is 2.37 percent per

Table 1—Summary Statistics by Turnover Type[a]

	Rent-to-rent turnovers[b]	Own-to-own turnovers[b]	Pooled renter and owner turnovers incl. tenure transitions[b]
Years between all turnover pairs[c]	4.17	7.18	4.47
Distribution of number of turnover pairs per home (percent)[c]			
1 pair (2 turnovers)	24.88	57.00	23.44
2 pairs (3 turnovers)	19.65	29.57	20.03
3 pairs (4 turnovers)	14.94	9.64	15.32
4+ pairs (5 or more turnovers)	40.53	3.79	41.21
log change in nominal income between turnover pairs[c]	0.063	0.157	0.074
log change in real income between all turnover pairs (US$(2011))[c]	−0.118	−0.075	−0.106
Age of home at time of turnovers (years)	37.37	31.06	36.04
Percent of homes that experience at least 1 tenure change	—	—	36.45
Distribution of tenure transitions across all turnovers (percent)			
Rent to rent	—	—	74.76
Own to own	—	—	16.85
Rent to own	—	—	3.31
Own to rent	—	—	4.06
Owner-occupancy rate across all home-year observations[d]			
All homes	—	—	67.7
Homes under 5 years in age	—	—	76.4
Homes age 5 to 50 years	—	—	68.7
Homes over age 50	—	—	64.1
Number of homes	19,041	9,789	28,072
Observations	56,139	13,782	72,170

[a] Additional summary measures for all of the variables used in the hedonic and housing demand models (Tables 2 and 5) are in the online Appendix.
[b] Sample restricted to observations on homes at the time the home turns over from one occupant to another. The Pooled sample in column 3 includes the sum of observations from rent-to-rent and own-to-own turnovers, plus additional turnovers in which the home changed tenure status (rent-to-own or own-to-rent).
[c] Each turnover pair is made up of two turnovers. At least one pair is necessary to estimate the repeat income model.
[d] Sample is based on the entire stock of homes over the sample horizon and includes all observations at the time of turnover and all observations between turnover dates.

Summary statistics for the key features of the sample are reported in Table 1. In the top row of the table, note that the average number of years between home turnovers is 4.17 for rental units and 7.18 for owner-occupied units. The faster turnover rate for rental units is consistent with well documented evidence that renters are mobile. Notice also that among homes belonging to the rent-to-rent sample, 24.88 percent experience just one pair of turnovers (or two turnovers) while 40.53 percent of the units have four or more pairs of turnovers. Among homes belonging to the own-to-own sample, 57 percent experience only one pair of turnovers and just 3.79 percent have four or more pairs of turnovers. I draw on these multiple turnover homes later in the article when estimating house fixed effect models.

year. If instead one excludes turnover pairs with initial arriving occupant income below $5,000 (in real terms) the analogous estimate is roughly 2.1 percent per year. Omitting turnover pairs for which *either* first- or second-arriving occupant income was nonpositive yields similar results. On the other hand, restricting second-arriving occupant income to nonpositive values without imposing restrictions on first-arriving occupant income truncates the distribution of possible filtering values from below and reduces filtering rates.

Table 1 also reports summary measures of the log change in arriving occupant income between turnover dates. With income expressed in nominal terms, the average log change in arriving occupant income is 6.3 percent for rental units and 15.7 percent for owner-occupied units. These values are obviously pushed upward by the general rate of inflation, masking possible filtering effects. Expressing income in real (US$ 2011) dollars, the average log change in arriving occupant income between turnover dates is negative 11.8 percent for rental units and negative 7.5 for owner-occupied units.[11]

These measures provide direct evidence that housing filters down, on average: there should no longer be debate on this point (e.g., Margolis 1982; Coulson and Bond 1990). However, the measures in Table 1 do not control for the time between turnover dates, and for that reason, the rate at which homes filter down is still unclear. In addition, to the extent that rental units filter faster than owner occupied, then the rate at which the total stock of housing filters down will be sensitive to any net tendency for homes to transition towards the rental sector as they age. Table 1 confirms such a tendency. Observe that for the pooled sample 36 percent of homes experience at least one change in tenure during the panel. In addition, 76.4 percent of recently built homes (under five years in age) are owner-occupied compared to 64.1 percent for homes over 50 years in age, and rental units are older than owner-occupied (37.4 years versus 31.1 years).[12] Given these patterns I allow for tenure transitions in some of the models to follow.

II. Depreciation Rates

Recall that low estimates of the rate at which house rents depreciate have contributed to doubt about the viability of filtering as a source of low-income housing. Table 2 reconfirms this result. Hedonic regressions of house rent and price are presented using initial-arrival observations from the sample of turnover pairs described earlier. The regressions control for an extensive set of house and neighborhood attributes in addition to metropolitan statistical area (MSA) and year fixed effects that allow for differences in rent (price) levels across MSAs and years.[13] Estimates are presented for all structure types pooled together, and also for multi- and single family homes separately. Only the coefficients on house age are reported in Table 2; complete regression results are in the online Appendix along with sample means of the model variables. The dependent variables are the log of gross house rent and the log of transaction price, respectively.

In Table 2, observe that house rents decline by 0.35 percent per year (column 1) for the full sample of rental units, 0.31 percent per year for multifamily rental units, and 0.51 percent per year for single family rentals. These estimates are consistent with other estimates in the literature.[14] For owner-occupied units depreciation rates

[11] The AHS also asks occupants to rate their level of "satisfaction" with the housing unit on a scale of 1 (worst) to 10 (best). The average change in the satisfaction index between turnovers is −0.040 for rentals and −0.062 for owner-occupied homes, consistent with the downward filtering of income as described above.

[12] Across all observed turnovers, 4.06 percent are own-to-rent while 3.31 percent are rent-to-own.

[13] Only the largest 146 MSAs are identified in the AHS data. Observations not in those locations are coded as belonging to a 147th less densely developed location and are retained in the regressions.

[14] See, for example, Margolis (1982); Bond and Colson (1989); Chinloy (1979); Smith (2004); and Wilhelmsson (2008). Leigh's (1980) estimates tend to be higher.

Table 2—Hedonic Regressions of House Rent and House Price

	Rental units: log of gross rent			Owner-occupied units: log of sale price		
	All	Multifamily	Single family	All	Multifamily	Single family
House age (years)	−0.0035**	−0.0031**	−0.0051**	−0.0084**	−0.0051*	−0.0090**
	(0.0002)	(0.0002)	(0.0006)	(0.0012)	(0.0022)	(0.0012)
Structural attributes[a]	Yes	Yes	Yes	Yes	Yes	Yes
Neigh attributes[a]	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	147	147	139	147	103	147
Year FE	27	27	27	27	27	27
Within R^2	0.159	0.131	0.226	0.446	0.128	0.298
Observations	56,139	44,280	10,417	13,782	1,583	10,946

[a] Structural features include structure type (single family detached, single family attached, multifamily, mobile homes), whether a garage is present, number of rooms, number of bathrooms, whether there are bars on some of the windows. Neighborhood features include whether some of the buildings within one-half block have bars on the windows, whether tall buildings are present within one-half block (seven or more stories tall, four to six stories tall, and less than four stories tall), and whether the home is on a waterfront location. For rental units additional controls are provided for whether the unit is owned by the government (i.e., public housing), and whether rent controls are in force. The complete results from the hedonic regressions are provided in the online Appendix.

Standard errors clustered at the MSA level in parentheses.

**Significant at the 1 percent level.

*Significant at the 5 percent level.

are higher: 0.84 percent for all homes, 0.51 percent for multifamily, and 0.9 percent for single family. Extrapolating using the full-sample depreciation rates, a 50-year-old rental unit rents for 83.9 percent of a newly built home, while a typical 50-year-old owner-occupied unit sells for 65.6 percent of a newly built home. Based solely on these estimates, one could conclude that filtering is quite limited as a long term source of affordable housing. As will be shown, that would not be correct.

III. The Repeat Income Model

A. *Econometric Specification*

As noted earlier, the core empirical strategy is motivated by widely used repeat sales methods (e.g., Bailey, Muth, and Nourse 1963; Case and Shiller 1989; Case and Quigley 1991; Harding, Rosenthal, and Sirmans 2007). Suppose that a home turns over twice and that we observe the income (Y) of the new occupant at each turnover. In the model below, turnover "dates" are measured based on the age in years of the home at the time of a given turnover. Thus, if a home is ten years old at the time of a sale or turning over of a rental unit, the "date" of that turnover is said to be ten years.

Consider now two successive turnovers at ages t and $t + \tau$ years, respectively. For each of these turnovers, the income of the arriving occupant can be written as

$$Y_t = e^{\gamma_t} f(\mathbf{X}_t; \beta_t), \tag{1a}$$

$$Y_{t+\tau} = e^{\gamma_{t+\tau}} f(\mathbf{X}_{t+\tau}; \beta_{t+\tau}), \tag{1b}$$

where $f(\mathbf{X}; \beta)$ is an unknown and potentially nonlinear function of the structural and neighborhood characteristics of the home $(\mathbf{X})$ and their shadow prices (β).

The terms γ_t and $\gamma_{t+\tau}$ are the parameters of interest and reflect the difference in income of arriving occupants as the home ages. If $\mathbf{X}$ and $\boldsymbol{\beta}$ are unchanged between the time the home is t and $t + \tau$ years in age, taking logs and rearranging gives the log change in arriving occupant income between turnovers,

$$(2) \qquad \log\left(\frac{Y_{t+\tau}}{Y_t}\right) = \gamma_{t+\tau} - \gamma_t + \omega_{t+\tau},$$

where ω is a random error term and $f(\mathbf{X}; \boldsymbol{\beta})$ drops out of the model. For a sample of properties $(i = 1, \ldots, n)$ that experience turnovers at various ages, the model in (2) becomes

$$(3) \qquad \log\left(\frac{Y_{t+\tau,i}}{Y_{t,i}}\right) = \sum_{t=1}^{\tau_i} \gamma_t D_{t,i} + \omega_{t,i} \qquad \text{for home } i = 1, \ldots, n,$$

where D_t equals -1, 0, or 1 depending on whether a given property of age t turns over for the first time, does not turn over, or turns over for the second time, respectively.

Equation (3) is analogous to the standard repeat sales specification. Notice that time invariant house and neighborhood attributes difference away. The γ parameters can then be estimated by regressing the log change in income for arriving occupants between turnover dates on the vector $\mathbf{D}$. Provided that $\mathbf{X}$ and $\boldsymbol{\beta}$ are unchanged between turnover dates, estimates of the $\boldsymbol{\gamma}$-vector indicate the rate at which a home filters down—or up—as it ages.

B. *Estimates*

Figure 1 displays plots of the repeat income indexes based on the model specification in (3) with arriving occupant income expressed in 2011 (constant) dollars. To simplify interpretation, the plotted indexes have been raised to base-e and shifted additively by an amount that sets the initial index value to 1.0. Panel A displays estimates for rental units, while panel B displays values for owner-occupied homes. Also plotted are the 95 percent confidence bands based on robust standard errors. In each panel, age of the housing unit is on the horizontal axis, while the vertical axis indicates the percentage difference in arriving-occupant income for a house of a given age in comparison to that of a newly built home.

Observe that in both panels, the plots are downward sloping and convex. This confirms that for both rental and owner-occupied housing, older homes tend to be passed down to families of lower income, and that filtering is relatively rapid when a home is young but slows as it ages. It is also clear that filtering rates are notably faster for rental units (panel A) versus owner-occupied units (panel B): 70 percent in the first 50 years versus 30 percent for owner-occupied homes. Filtering of rental units also proceeds at a much faster pace than depreciation of rents: recall that a simple extrapolation of estimates in Table 2 suggests that rents on a 50-year-old home are just 16 percent lower than for a newly built unit.

The patterns in Figure 1 are striking and also point to further questions. Most obvious, why are the plotted indexes convex, and why are rental filtering rates so

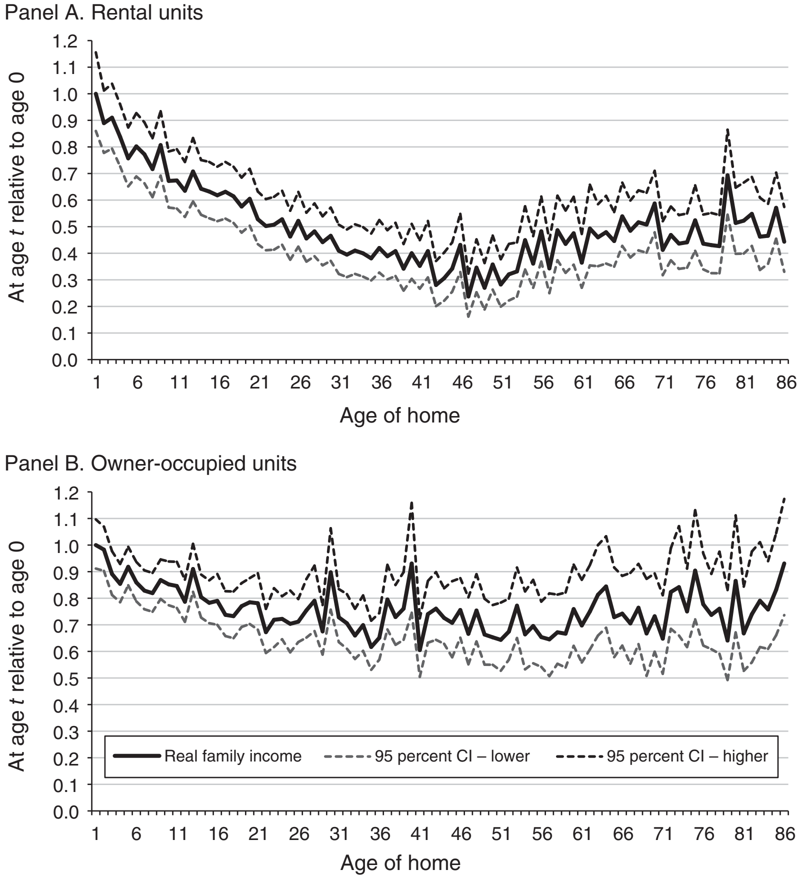

FIGURE 1. REPEAT INCOME INDEXES (γ) WITH INCOME ADJUSTED FOR INFLATION TO YEAR 2011 DOLLARS

Note: Based on $\log\left(\frac{Y_{t+\tau,i}}{Y_{t,i}}\right) = \sum_{t=1}^{\tau_i} \gamma_t D_{t,i} + \omega_{t,i}$ from equation (3).

rapid? Survivor effects may help to answer the first question: homes that survive to an old age likely possess unobserved attributes that enhance their physical and/or economic durability and slow the rate at which older homes are observed to filter down.[15] Nevertheless, few homes are demolished before age 50, while the plots in Figure 1 tend to flatten out beginning at about age 40. The central patterns in Figure 1, therefore, seem likely to be robust to survivor effects which, if anything, would slow the rate of filtering. The key question, therefore, is why are rental housing filtering rates so high relative to depreciation rates and owner-occupied homes?

[15] Previous studies have confirmed, for example, that homes tend to be demolished when they become sufficiently obsolete and/or dilapidated. See Dye and McMillen (2007); Brueckner and Rosenthal (2009); McMillen and O'Sullivan (2013); Rosenthal (2008); and Rosenthal and Helsley (1994).

IV. Model Based Estimates

A. *Housing Demand*

To help explain the puzzle above, consider the following simple housing demand function:

$$\log(h_{t,i}) \;=\; \theta_Y \log(Y_{t,i}) \;+\; \theta_q \log(q_{t,i}). \tag{4}$$

Implicit in this specification is the assumption that housing can be decomposed into homogenous quality adjusted units, the sum of which is denoted by h. For a sample of renter-occupied units, the rent per unit of housing—on a quality adjusted basis—is given by q, while the parameters θ_Y and θ_q are the income and price elasticities of demand for housing, respectively. For a sample of owner-occupied units, q would be the quality adjusted price. Many estimates of housing demand based on the specification in (4) can be found in the literature (e.g., Rosen 1979; Hoyt and Rosenthal 1990).

Solving for $\log(Y)$ in (4), differencing across turnover dates, and imposing a constant annual rate of depreciation d (i.e., $\log(h_{t+\tau,i}/h_{t,i}) = d\tau_i$) yields an alternate expression for $\log(Y_{t+\tau,i}/Y_{t,i})$,

$$\log\left(\frac{Y_{t+\tau,i}}{Y_{t,i}}\right) \;=\; \frac{d}{\theta_Y}\tau_i \;-\; \frac{\theta_q}{\theta_Y}\log\left(\frac{q_{t+\tau,i}}{q_{t,i}}\right) \;+\; \omega_{t,i}. \tag{5}$$

From expression (5) it is clear that filtering rates depend on both the rate at which housing depreciates (d) and the drivers of housing demand. In this regard, several principles are worth highlighting.

First, house price inflation (indicated by a change in q) slows the rate at which homes filter and can even cause homes to filter up instead of down. This follows because $-\theta_q/\theta_Y > 0$ given a downward sloping demand function ($\theta_q < 0$) and that the income elasticity of demand is positive ($\theta_Y > 0$). Because house price inflation differs across locations, filtering rates should as well.

Second, in the absence of house rent (price) inflation ($q_t = q_{t+1}$), for a given rate at which housing capital depreciates (d), the rate at which a home filters down varies inversely with the income elasticity of demand, $d/\theta_Y < 0$. This is because housing is a normal good. Thus, as the flow of services from a home declines the willingness to pay for the home declines more quickly for higher income families. This increases the tendency for low-income families to outbid high-income households for older housing and accelerates filtering (e.g., Bond and Coulson 1989 and Brueckner and Rosenthal 2009).

Third, setting τ to 1 to denote a one-year passage of time, the overall marginal effect of the income elasticity of demand on the annual rate of filtering is

$$\frac{\partial \log(Y_{t+1}/Y_t)}{\partial \theta_Y} \;=\; -\frac{1}{\theta_Y^2}\left[d \;-\; \theta_q \log(q_{t+1}/q_t)\right], \tag{6}$$

where the i subscripts are dropped for convenience, and $\log(q_{t+1}/q_t)$ is the rate of house price inflation. The sign of this derivative depends on the magnitude of d relative to $\theta_q \log(q_{t+1}/q_t)$ since $d < 0$ and $-\theta_q > 0$. A long literature on housing demand suggests that θ_q is likely in the neighborhood of -0.5, at least as a rough approximation. House price inflation, $\log(q_{t+1}/q_t)$, can be measured using quality adjusted house price indexes from the Federal Housing and Finance Agency (FHFA).[16] Based on census region-level FHFA house price indexes, over the 1975–2011 period the real annualized rate of house price inflation was close to zero for much of the country.[17] This suggests that $\theta_q \log(q_{t+1}/q_t)$ is small relative to d and that an income elasticity below 1 amplifies the rate of downward filtering by a factor approximately equal to $1/\theta_Y^2$. This helps to explain why rental filtering rates are high relative to rent depreciation rates.[18]

B. *House Rent* (*Price*) *Inflation*

In order to estimate (5) it is necessary to control for house rent (price) inflation, $\log(q_{t+\tau,i}/q_{t,i})$, where q is the quality adjusted rent (price) per unit of housing. One strategy is to proxy for $\log(q_{t+\tau,i}/q_{t,i})$ with $\log(p_{t+\tau,i}/p_{t,i})$, where p is the observed actual rent (sale price) for a given home. While convenient, this should yield downward biased estimates of age-related filtering. To see why, note that $p = qh$ given the variable definitions above and suppose that h depreciates at a linear rate as before. Then,

$$\log(p_{t+\tau,i}/p_{t,i}) = \log(q_{t+\tau,i}/q_{t,i}) + d\tau_i. \tag{7}$$

Rearranging (7) and substituting into (5) gives

$$\log\left(\frac{Y_{t+\tau,i}}{Y_{t,i}}\right) = \frac{d}{\theta_Y}(1 + \theta_q)\tau_i - \frac{\theta_q}{\theta_Y}\left[\log\left(\frac{p_{t+\tau,i}}{p_{t,i}}\right)\right] + \omega_{t,i}, \tag{8}$$

where d/θ_Y is scaled by $(1 + \theta_q)$. With $\theta_q < 0$, OLS applied to (8) yields downward biased estimates of d/θ_Y.

To address this issue, I instrument for the actual change in house rent (price) using MSA-level FHFA repeat sales (quality adjusted) house price indexes. Because the FHFA indexes are formed at a higher level of geography than the individual house, they are independent of house-specific attributes that might be correlated with changes in arriving occupant income, and therefore, the model error term. This helps to ensure that the FHFA indexes are exogenous. In addition, estimates to be reported below confirm that the FHFA indexes are strongly correlated with observed changes in house rents and prices. For these reasons, instrumenting with the FHFA

[16] See the house price index link at www.fhfa.gov for details.

[17] See Table 6 for details which will be discussed later in the article.

[18] A further implication of (5) is that if $\log(q_{t+1}/q_t)$ and τ are correlated, then failing to control for house rent (price) inflation could bias estimates of age-related filtering. For that reason, in the estimation to follow I control for $\log(q_{t+1}/q_t)$. Nevertheless, it is worth noting that the sample correlation between $\log(q_{t+1}/q_t)$ and τ appears to be small: for rental units 5.26 percent for rents, and for owner-occupied units 7.57 percent for price. The weak correlation will reduce biases if rent (price) effects are ignored. These issues are also relevant when estimating repeat sales indexes if high-turnover homes appreciate at unusual rates (e.g., Gatzlaff and Haurin 1997).

Table 3—Real Change (log) in Arriving Occupant Income[a]

	OLS (1)	OLS (2)	OLS (3)	2SLS[b] (4)	OLS[d] (5)
Panel A. Renter occupied					
Years between turnover (d/θ_Y)	−0.0181**	−0.0194**	−0.0237**	−0.0271**	−0.0299**
	(0.0022)	(0.0021)	(0.0018)	(0.0020)	(0.0027)
Percent change in FHFA Index[c]	—	—	0.2522**	—	0.2528**
	—	—	(0.0489)	—	(0.0368)
log change in rent (θ_q/θ_Y)	—	0.1876**	—	1.289**	—
	—	(0.0105)	—	(0.1374)	—
MSA fixed effects	147	147	147	147	—
House fixed effects	—	—	—	—	12,861
KP weak inst. F-statistic	—	—	—	270.98	—
First-stage coeff on %ΔFHFA index	—	—	—	0.1957**	—
	—	—	—	(0.0302)	—
Root MSE	1.289	1.286	1.289	1.403	1.409
Observations	56,139	56,139	56,139	56,139	49,959
Panel B. Owner occupied					
Years between turnover (d/θ_Y)	−0.0027	−0.0030*	−0.0058**	−0.0049**	−0.0007
	(0.0014)	(0.0013)	(0.0018)	(0.0014)	(0.0047)
Percent change in FHFA Index[c]	—	—	0.1744**	—	0.2310**
	—	—	(0.0523)	—	(0.0819)
log change in price (θ_q/θ_Y)	—	0.0899**	—	0.2485**	—
	—	(0.0115)	—	(0.0563)	—
MSA fixed effects	146	146	146	146	—
House fixed effects	—	—	—	—	2,953
KP weak inst. F-statistic	—	—	—	335.39	—
First-stage coeff on %ΔFHFA index	—	—	—	0.8012	—
	—	—	—	(0.0555)	—
Root MSE	1.047	1.031	1.046	1.039	1.171
Observations	13,781	13,206	13,781	13,206	6,946

[a] Estimates are based on expression (5) in the text.
[b] log change in rent (price) are treated as endogenous. The change in the FHFA home purchase house price index between turnover dates is used as the instrument. Complete first-stage results are reported in the online Appendix.
[c] Calculated as the FHFA house price index in period t divided by the index in period $t - \tau$, where t is the year the home turns over and τ is the time since previous turnover.
[d] The number of observations in the house fixed effects models are reduced relative to the corresponding MSA fixed effects models because of singleton observations.
Standard errors clustered at the level of the indicated fixed effects in parentheses.
**Significant at the 1 percent level.
*Significant at the 5 percent level.

indexes should reduce bias associated with the extra $d\tau$ term in (8) and yield higher estimates of age-related filtering, a pattern confirmed in the data.[19]

C. *Rental and Owner-Occupied Filtering Rates*

Estimates of the models above are presented in Table 3 with arriving occupant income expressed in real (constant dollar) terms. Panel A reports estimates for rental

[19] The primary reason to be cautious of the FHFA instrument is that income drives housing demand and may affect price. Although measuring income at the individual level mitigates this concern, I cannot rule out the possibility that macroeconomic shocks could affect the change in individual occupant income and the FHFA price index.

units. Notice that column 1 displays OLS estimates controlling for the time between turnovers and MSA fixed effects.[20] Column 2 adds the actual change in rent between turnovers as a control. Column 3 replaces the actual change in rent with the change in the FHFA index. Column 4 reestimates column 3 by 2SLS using the percent change in the FHFA index as a first-stage instrument for the log change in rent. Column 5 also reestimates column 3, but this time by OLS and with house fixed effects instead of MSA fixed effects. Panel B reports analogous models for owner-occupied units.

Observe first that for both the rental and owner-occupied samples, the FHFA index is highly significant when entered as a direct control measure and overwhelmingly strong as an instrument when used in the 2SLS models. The former is evident from the very low standard errors on the FHFA index coefficients in columns 3 and 5. The latter is evident from diagnostics statistics at the bottom of column 4 in both panels, including the very large Kleibergen-Paap weak instrument statistics, and very low standard errors on the first-stage coefficients on the change in the FHFA index. This eliminates any concern about weak instrument bias (e.g., Stock and Yogo 2005). The first-stage FHFA coefficient also corresponds to priors: because the index measures the percent change in quality adjusted house prices, its first-stage coefficient should be close to 1 for the owner-occupied regressions and positive for the rental regressions. These conditions are met with respective coefficients of roughly 0.8 and 0.2.

Consider now the estimated filtering rates among rental units in panel A of Table 3. The coefficient on the time between turnovers in column 1 is 1.81 percent per year and highly significant. Controlling for the actual change in house rent between turnovers (column 2) increases the magnitude of that coefficient to 1.94 percent per year. Replacing the log change in actual house rent with the change in the FHFA index in column 3 increases the magnitude of the filtering coefficient further, to 2.37 percent per year, and to 2.7 percent when estimating by 2SLS.[21] These latter two estimates are consistent with the anticipated downward bias associated with use of the actual log change in rent as discussed earlier. Finally, column 5 is estimated by OLS and includes house fixed effects that sweep out unobserved time-invariant factors that might cause estimates of filtering rates to be downward biased as discussed in the context of Figure 1.[22] The filtering rate for this model is 2.99 percent per year, which is higher than in column 3, the relevant counterfactual, and as anticipated.

Analogous estimates for owner-occupied homes are reported in panel B. For this sample the house fixed effect model suffers from noisy estimates because there are too few multiple turnover pairs in the data. For that reason, results from the MSA fixed effect models are likely more reliable. The dominant pattern that emerges from panel B is clear: filtering rates are much lower for owner-occupied homes. As an example, the estimate in column 3, which controls directly for the FHFA index,

[20] Recall that 146 metropolitan statistical areas (MSAs) are identified in the AHS data. All non-MSA locations are grouped together for a final, 147th area.

[21] In panel A, because the models in columns 3 and 4 both rely on the FHFA index, their information content is the same, and they both yield consistent estimates of age-related filtering. However, whereas the 2SLS model (column 4) yields consistent estimates of the rent effects, the OLS approach (column 3) yields consistent estimates of the rent effect multiplied by the first-stage coefficient on the FHFA index from the 2SLS model. The same is true in panel B for the owner-occupied sample. The coefficients reported in Table 3 satisfy these conditions.

[22] Suppose, for example, that brick homes are more durable and slow the rate of filtering. The house fixed effects control for such effects and should cause the estimated filtering rate to increase.

Table 4—Real Change (log) in Arriving Occupant Income Allowing for Tenure Transitions[a]

	Turnovers with a change in tenure	Turnovers without a change in tenure	All turnovers	All turnovers	All turnovers[c]
Years between turnover	−0.0306**	−0.0176**	−0.0173**	−0.0185**	−0.0289**
	(0.0063)	(0.0014)	(0.0016)	(0.0016)	(0.0023)
Percent change in FHFA Index[b]	0.3043**	0.2423**	0.2422**	0.2483**	0.2572**
	(0.1127)	(0.0448)	(0.0447)	(0.0461)	(0.0329)
Change tenure from rent to own	—	—	0.2802**	—	—
	—	—	(0.0221)	—	—
Change tenure from own to rent	—	—	−0.2319**	—	—
	—	—	(0.0246)	—	—
MSA fixed effects	132	147	147	147	—
House fixed effects	—	—	—	—	16,706
Root MSE	1.260	1.235	1.235	1.236	1.367
Observations	3,947	68,213	72,170	72,170	60,804

[a] Estimates are based on expression (5) in the text adjusted to allow for tenure transitions.
[b] Calculated as the FHFA house price index in period t divided by the index in period $t - \tau$, where t is the year the home turns over, and τ is the time since previous turnover.
[c] The number of observations in the house fixed effects models are reduced relative to the corresponding MSA fixed effects models because of singleton observations.
Standard errors clustered at the level of the indicated fixed effects in parentheses.
** Significant at the 1 percent level.
* Significant at the 5 percent level.

implies a filtering rate of negative 0.58 percent per year, well below estimates for rental housing.

D. *Tenure Transitions and Total Housing Stocks*

The models above confirm that housing filters down and that rental units filter faster than owner occupied. While informative, those estimates do not measure the rate at which the *total stock* of housing filters down. To do that requires that one control for tenure transitions and also the relative concentration of homes in the two housing sectors.

To take these considerations into account, the repeat income models were reestimated using pooled samples of owner-occupied and rental units. Results are presented in Table 4 for five different specifications. Notice that all of the specifications control for the change in the FHFA index between turnovers, the coefficient for which is always positive and significant as before.

In column 1, estimates are obtained using only observations for which tenure status changed upon turnover and controlling for MSA fixed effects. The estimated filtering rate is negative 3.06 percent per year. Column 2 uses only homes for which no tenure transitions occur. This yields a filtering rate of negative 1.76 percent per year. The model in column 3 pools all observations on turnovers and includes controls for whether a home shifts from rent to own at turnover or from own to rent. The estimated filtering coefficient is nearly identical to the column 2 estimate. This is as anticipated since the omitted tenure-change category is no change in tenure status. The tenure transition coefficients in model 3 further indicate that upon changing tenure, there is a discrete increase in arriving occupant income for rent-to-own transitions of 28 percent and a similar magnitude decrease for transitions going from own to rent.

Column 4 repeats the model from column 3 but without the tenure transition variables. The estimated filtering rate is 1.85 percent per year. Using house fixed effects as in column 5 increases that rate to 2.89 percent per year. This is likely the most robust measure of the rate at which the nation's housing stock filters down, in that it allows for tenure transitions while also controlling for unobserved house-specific attributes.

E. *Testing the Model Structure*

A core feature of the model in (5) is that in the absence of house rent (price) inflation, homes should filter down at a rate given by $\gamma = d/\theta_Y$, where γ is the coefficient on τ (the time between turnovers), d is the rate at which house rent (price) depreciates, and θ_Y is the income elasticity of demand for housing. In addition, house price inflation contributes to filtering in proportion to the ratio of the price to the income elasticity of demand for housing, $-\theta_q/\theta_Y$ (the coefficient on the log change in q). This section considers evidence for and against that structure.

Consider first the influence of house rent (price) inflation. Given strong priors that $\theta_q < 0$ and $\theta_Y > 0$, the ratio $-\theta_q/\theta_Y$ should be positive. This is confirmed in Tables 3 and 4 where the coefficients on the change in rent, price, and the FHFA indexes are all positive and generally highly significant.

Consider next the idea that as homes age, they filter down at a rate given by the ratio of the depreciation rate to the income elasticity of demand, $\gamma = d/\theta_Y$. To test this relationship requires that one estimate a housing demand model, which I do in Table 5 for both rental and owner-occupied units. The key control variable is the log of current real (US\$ (2011)) family income for the initial arriving occupant in a turnover pair. Additional standard controls for socioeconomic attributes are included in the models but are suppressed in the table.[23] In considering the estimates in Table 5, note that rent (price) of housing is assumed to vary across MSA and years and is captured by inclusion of MSA and year fixed effects.[24]

In Table 5, the estimated income elasticities are 12.4 percent for renters and 41.3 percent for owner occupiers (these estimates are also highly significant). This confirms that the income elasticity of demand for housing for homes in the AHS is well below 1 as in previous studies. An implication is that homes should filter down faster than the rate at which they depreciate. Moreover, that difference should be greater for rental housing than owner-occupied given the much lower income elasticity of demand in the rental sector of the market. This helps to explain how rental homes can filter down so much faster than owner occupied (as in Figure 1 and Table 3) despite the slower rate at which rent depreciates relative to price (as in Table 2). Once again, the qualitative implications of the model are supported.

Despite the coherence of these results, Wald tests reject the null that reduced-form estimates of γ are equal to model-based values implied by estimates of d and θ_Y in Tables 2 and 5. To check this, I reestimated the filtering, hedonic, and housing demand

[23] The complete set of results for the housing demand models are presented in the online Appendix along with summary measures of the variables in the models. Results conform to priors and previous findings in the literature.

[24] Previous studies based on samples of owner occupiers have relied on favorable tax treatment of homeownership and differences in tax rates across households to generate cross-sectional variation in housing price (e.g., Rosen 1979; Hoyt and Rosenthal 1990; Rosenthal, Duca, and Gabriel 1991). That approach does not work for rental units. Partly for that reason, I proxy for variation in rent (price) using MSA and year fixed effects.

Table 5—Housing Demand Regressions

	Renter occupied (Dep. var.: log rent)	Owner occupied (Dep. var.: log price)
log family income (θ_Y)	0.1236**	0.4126**
	(0.0098)	(0.0349)
Socioeconomic household attributes[a]	Yes	Yes
MSA fixed effects	147	147
Year fixed effects	27	27
Within R^2	0.150	0.254
Observations	56,139	13,782

[a] Additional controls include age of household head, marital status, and gender of household head (married, single female, single male), whether school age children are present, race (whether the household head is white, black, Asian, Hispanic, or other), education (whether the household head has more than a college degree, college degree, some college, high school degree, less than high school degree). Complete results for the housing demand regressions are reported in the online Appendix.

Standard errors clustered at the MSA level in parentheses.

** Significant at the 1 percent level.

* Significant at the 5 percent level.

models as a three-equation SUR system with d and θ_Y set to their full-sample model estimates from Tables 2 and 5: -0.0035 and 0.1235 for rental units, and -0.0084 and 0.4126 for owner-occupied units.[25] Forming d/θ_Y, these values imply model-based estimates of γ equal to -0.0283 and -0.0204 for the rental and owner-occupied sectors, respectively. In comparison, the SUR model estimates of γ were lower, -0.0191 for rental units and -0.0035 for owner occupied, and the corresponding Wald test statistics (with a chi-square (1) distribution) were 29.55 and 78.75.[26]

For several reasons, it is not surprising that the model structure embodied in $\gamma = d/\theta_Y$ is rejected despite the qualitative support for the model described above. The first is that the plots in Figure 1 strongly suggest that age-related filtering proceeds at a nonlinear pace as homes age, and for that reason, the linear rate of depreciation specification in (5) cannot be exact. Second, and related, the model outlined in (5) depends on a simple specification of housing demand that likely understates the complexity of the true functional form. For these and other reasons, I believe that the model structure in (5) is best characterized as a useful approximation that illuminates two important features of the filtering process.[27] Those principles include that (i) the influence of depreciation on filtering rates is amplified by the income elasticity of demand given numerous plausible estimates which place that elasticity well below 1, and (ii) filtering rates vary inversely with house price inflation and therefore differ across locations.

[25] The SUR models for the rental and owner-occupied units used the same specifications for the full-sample hedonic models in Table 2 and the demand functions in Table 5. The filtering equations were specified as in column 3 of Table 3.

[26] Additional evidence that the model structure is likely not exact is obtained by backing out the price elasticity of demand for housing (θ_q) implied by estimates of θ_q / θ_Y from Table 3 and θ_Y from Table 5. To do this, multiply the income elasticities from Table 5 by the coefficients on the log change in rent (price) in column 4 of panels A and B in Table 3. This yields estimates of θ_q of 15.92 percent for rental units and 10.25 percent for owner occupied. Especially for owner-occupied housing, for which there are many estimates of θ_q in the literature, the implied price elasticity is low.

[27] Other reasons why the model fails a formal test are that current rather than permanent income is used in estimating the housing demand models, and the large sample increases the power to reject the null.

TABLE 6—SIMULATED REAL ANNUALIZED FILTERING RATES 1975–2011 ALLOWING FOR HOUSE PRICE INFLATION

		Filtering rates by housing tenure		
	Annualized real % change in house price (1975 to 2011)[a] (1)	Renter occupied[b] (2)	Owner occupied[b] (3)	Pooled renter and owner occupied allowing for tenure transitions[b] (4)
USA	0.66	−2.20	−0.48	−1.69
New England	2.02	−1.86	−0.25	−1.35
Middle Atlantic	1.26	−2.05	−0.38	−1.54
South Atlantic	0.35	−2.28	−0.54	−1.76
East South Central	−0.07	−2.39	−0.61	−1.87
East North Central	0.02	−2.37	−0.60	−1.85
West South Central	−0.08	−2.39	−0.61	−1.87
West North Central	0.21	−2.32	−0.56	−1.80
Mountain	0.46	−2.25	−0.52	−1.74
Pacific	2.24	−1.81	−0.21	−1.29

[a] Calculated by annualizing the FHFA all transactions (home purchase plus appraisals) house price index 1975–2011 deflated by the CPI-U.
[b] The reported filtering rates were obtained by combining the coefficients from the repeat income models for the rental, owner-occupied, and pooled samples (column 3, panels A and B of Table 3 and column 4 of Table 4) with the column 1 measure of house price inflation:

- Renter-occupied (column 2) filtering rates = −0.0237–0.2522*(column 1).
- Owner-occupied (column 3) filtering rates = −0.0058–0.1744*(column 1).
- Pooled sample (column 4) filtering rates = −0.0185–0.2483*(column 1).

V. Simulations

As a final exercise, this section highlights the degree to which house price inflation contributes to filtering. For these purposes, I draw upon the 1975 to 2011 change in the FHFA home purchase index for the United States and its nine census regions. Annualized values for the real change in the 1975–2011 indexes are reported in column 1 of Table 6. Filtering rates were then simulated by applying the annualized changes in the FHFA index to the repeat income coefficients in Tables 3 and 4 for the rental, owner-occupied, and pooled housing stocks. This was done using the MSA fixed effect specifications that include the FHFA index as a direct control for rent (price) changes between turnovers (column 3 in panels A and B of Table 3 and column 4 of Table 4). Higher filtering rates would be obtained using the house fixed-effect models, but those models are imprecise for the owner-occupied sector as discussed earlier.

As shown in Table 6, at the national level the annualized real rate of house price inflation (in column 1) between 1975 and 2011 was 0.66 percent. That rate is too low for house price inflation to have much effect on the overall rate at which homes filter down. The coefficient on the change in the FHFA price index is approximately 0.2 for the relevant models in Tables 3 and 4. Adjusting the filtering rate by the product of 0.2 and 0.66 reduces the rate at which housing filters down by just 0.13 percentage points. This suggests that for most of the nation, the long-run rate of filtering has been driven almost entirely by age-related effects with only modest influence from house price inflation.

There are exceptions, however. As reported in Table 6, the annualized rate of house price inflation between 1975 and 2011 was roughly 2 percent real per year in the New England and Pacific divisions. At that rate homes filter down roughly

0.5 percent more slowly per year given the coefficient estimates on the FHFA price index in Tables 3 and 4. Even larger effects arise for select metropolitan areas with unusually large rates of house price inflation.

Summarizing, filtering rates vary inversely with the rate of house price (rent) inflation. However, over the four-decade period from 1975–2011, real house price inflation has been modest for most of the United States, and especially outside of New England and the West. During this period, age-related depreciation of the housing stock has been the dominant driver of filtering in most regions. It is also true that filtering rates are noticeably lower in locations subject to more rapid rates of house price inflation, as with areas subject to land supply constraints. This contributes to variation in filtering rates across areas and suggests that filtering may not be a reliable source of lower income housing in all areas.

VI. Conclusions

Remarkably, direct estimates of the rate at which individual homes filter down to lower income families have been largely absent. That absence along with documented low rates of house rent and price depreciation have contributed to doubts about the ability of private markets and filtering to serve as a robust long-run source of lower income housing (e.g., Margolis 1982; Coulson and Bond 1990). This has also likely contributed to misplaced housing assistance policy, including subsidized construction of lower-income housing in areas where filtering rates have been high. This article addresses these issues by providing the first ever direct measures of filtering rates.

Central to my analysis, I develop a new econometric methodology based on a modification of popular repeat sales methods (e.g., Case and Shiller 1989), which I refer to as a “repeat-income” model. Extensions of the core model suggest that filtering rates are amplified as the income elasticity of housing demand falls below one for a given rate of house rent (price) depreciation. Filtering rates also vary inversely with house price inflation which contributes to differences in filtering rates across locations.

Findings indicate that between 1975 and 2011, the real average annual rate of filtering for owner-occupied homes has been low—roughly 0.5 percent per year. This would seem to provide support for skeptics of the filtering process. In the rental sector—which is the traditional home of lower-income families—filtering rates are much faster and have likely ranged between 1.8 and 2.5 percent per year (in constant dollars) depending on the local real rate of house price inflation. It is also important to recognize that homes display a net tendency to transition into the rental sector as they age. Estimates of the rate at which the total stock of housing filters down must allow for such transitions given that roughly 80 percent of newly built homes are owner occupied, but filtering rates are faster in the rental segment of the market. Taking these effects into account, the nation’s housing stock filters down at a rate of roughly 1.9 percent per year in real terms. At that rate, the real income of an arriving occupant in a 50-year-old home would be 60 percent less than the income of an occupant of a newly built home. These estimates confirm that filtering is a viable long-run market-based source of lower-income housing.

For housing assistance advocates a message is to take seriously the market’s ability to generate lower-income housing, especially among rental units. This lends support to housing voucher programs that rely on market supplies of affordable housing but with the caveat that filtering is less pronounced in areas subject to high rates of house price appreciation.

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