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

Stuart S. Rosenthal
Maxwell Advisory Board Professor of Economics
Department of Economics and Center for Policy Research
Syracuse University
Syracuse, NY 13244-1020
Phone: (315) 443-3809
Email: ssrosent@maxwell.syr.edu
http://faculty.maxwell.syr.edu/rosenthal/

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Abstract

While filtering has long been thought to be 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 also to misplaced policy. I address these issues by estimating a "repeat income" model using 1985-2009 panel data. Findings indicate that rental housing filters down at an average real annual rate of 2 percent. Filtering rates are slower for owner-occupied housing and also vary inversely with house price inflation. For most locations, findings lend support for market-based housing voucher programs over subsidized construction.

JEL Codes: R0, R21, R31
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1. Introduction

Debate about how best to provide housing assistance for low-income families has persisted for decades. Should government emphasize tenant-based voucher programs in which families seek housing in the private market, or should government subsidize the construction of low-income units as with public housing and the Low Income Housing Tax Credit (LIHTC) program (e.g. Eriksen and Rosenthal (2010))? Implicitly, this debate centers around doubt about the private market's ability to supply low-income housing. It has long been recognized, for example, that the private market builds little unsubsidized housing for the poor (e.g. Baer (1986)). Instead, the primary mechanism by which private markets are thought to provide low-income housing is through a dynamic process in which homes built for higher income families gradually deteriorate and filter down to households of lower income status (e.g. Sweeney (1974), Ohls (1978)). The viability of this process as a source of low-income housing, however, has been questioned. In part, that is because hedonic studies typically find that the rate at which house rents (prices) depreciate with age is very low, often below 0.5 percent per year (e.g. Margolis (1982), Bond and Coulson (1990)).[1] Such low rates would seem to preclude the possibility that filtering could be relied upon as a robust long run source of low-income housing.

This paper makes several contributions that do much to resolve the question of whether and under what conditions filtering and the private market can be relied upon as a viable long term source of low-income housing. The first is to develop a new econometric methodology that provides the first-ever direct estimates of the rate at which homes are passed down to families of lower-income status. The second is more conceptual in nature and makes a point that has tended to be overlooked in much of the debate about the viability of filtering as a source of low-income housing. Based on a simple model of housing demand, I show that for any given rate at which homes depreciate, and in the absence of real

[1] Margolis estimates house price depreciation rates of roughly 0.3 percent per year. Bond and Colson fail to find evidence of depreciation in two of six cities examined, and low rates of depreciation in the remaining four. They also see little evidence that higher income families are drawn towards new homes, all else equal. Both studies conclude that the filtering process is not a viable source of low-income housing. Additional studies that describe low rates of house rent (price) depreciation include Chinloy (1979), Smith (2004), and Whilenssom (2008); Leigh's (1980) estimates tend to be higher. Hedonic estimates developed in this paper using the American Housing Survey (AHS) reinforce the typical finding of low rates of house rent (price) depreciation.

house price inflation, the rate at which homes filter down is amplified when the income elasticity of demand for housing is less than one. Moreover, the degree of amplification increases at a nonlinear rate as the income elasticity becomes smaller.[2] The model also makes clear that rising real quality adjusted housing rents and prices slow the rate of filtering while falling rents and prices have the opposite effect.

My empirical approach is motivated by panel repeat sales methods first developed by Bailey, Muth, and Nourse (1963) and refined and popularized by Case and Shiller (1989).[3] 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.[4] 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 in a manner that will be clarified later in the paper.

As will become apparent, the empirical design yields estimates of an index that measures the percentage difference in income of arriving occupants across turnover dates as the home ages, holding constant the time invariant features of the house (e.g. number of rooms, single family detached, etc.). The index is estimated in a flexible fashion that allows for filtering down and up, and also very general non-linear patterns in filtering rates as the home ages. Restricted versions of the model are also estimated that constrain the rate of filtering to be constant with each passing year. The restricted specifications permit additional modeling opportunities that highlight that filtering rates depend not only on the rate at which homes depreciate, but also on the underlying housing demand function and house rent and price inflation.

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[2] For related discussion of the relationship between household income and the equilibrium sorting of families into old and young homes, see Bond and Coulson (1989) and Brueckner and Rosenthal (2010). These papers examine the impact of household income on the maximum bid families are willing to make for homes of different age. Different from these studies, this paper offers an explicit, estimable expression for the relationship between depreciation rates, the income elasticity of demand, and the rate at which homes filter down.

[3] See also Case and Quigley (1991) and Harding et al (2007) for extensions of the basic repeat sales model.

[4] Harding et al (2007) emphasize that price indexes based on repeat sales models are excellent measures of the rate at which an existing stock of homes appreciates. However, because repeat sales methods do not typically control for age-related depreciation and home maintenance, indexes based on the repeat sales method may over- or understate the true quality adjusted rate of house price inflation.

As noted above, I show that in long run equilibrium, housing demand income elasticities below one amplify filtering rates for any given rate at which homes depreciate and in the absence of real house price inflation. It is worth emphasizing that previous estimates of the income elasticity of demand for housing are mostly well below one (e.g. Rosen (1979), Hoyt and Rosenthal (1990), and Rosenthal, Duca, and Gabriel (1991), Glaeser, Kahn, and Rappaport (2008)), a finding that is replicated later in this paper. Moreover, I show that for plausible values of the income elasticity of demand for housing and historical house price (rent) inflation, filtering rates could easily be several times higher than the rate at which homes depreciate. This helps to explain two seemingly inconsistent stylized facts: that most lower income families outside of public or LIHTC housing live in older homes (e.g. Rosenthal (2008)), and that house rents (prices) depreciate at very slow rates (e.g. Chinloy (1979), Margolis (1982), Bond and Coulson (1990), Smith (2004), Whilenssom (2008)).[5]

Data for the analysis are based on the national core files of the 1985-2009 American Housing Survey (AHS). The AHS is a unique panel that follows individual homes – not households – over time. Using these data, I estimate the repeat income model separately for owner-occupied and rental housing units. Additional information in the survey is also used to estimate traditional hedonic models of house rent and price for the rental and owner-occupied sectors. These models provide measures of the rate of house rent and price depreciation as the home ages. Housing demand models are also estimated yielding fresh estimates of the income elasticity of demand for housing. Together, these supplemental measures allow me to construct an alternative, more conceptually based estimate of filtering rates as will become apparent.

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[5] Bond and Coulson (1990) offer a different explanation for the pattern of stylized facts just noted. They emphasize that higher income families are drawn to homes with larger amounts of floor space, and that older homes are smaller. They argue that this helps to explain the observed tendency for lower income families to reside in older homes. It should be emphasized, however, that the estimates in this paper are based on a model that explicitly differences away the influence of broad features of the home, such as floor space. It is also worth noting that Bond and Coulson (1990) focus only on six cities (Atlanta, Baltimore, Chicago, Houston, Philadelphia, and Seattle) for 1979 and 1980. As will be made clear later in the paper, filtering rates differ across locations and time. It is also possible, therefore, that the cities and time period studies by Bond and Coulson are not indicative of the broader influence and role of filtering in the market.

Findings indicate that filtering is more rapid in the first forty years of a home's life, and slows thereafter. On average, age-related filtering is roughly -0.5 percent per year for owner-occupied homes when occupant income is expressed in real terms. When occupant income is measured relative to U.S. average income, the rate of filtering is faster, roughly 1.5 percent per year. For rental homes, the corresponding estimates are nearly 3.0 percent with income measured in real terms and 3-3/4 percent with occupant income measured relative to U.S. average income. These patterns are consistent with longstanding arguments that owner-occupiers have more incentive to maintain their homes than do owners of rental units (e.g. Henderson and Ioannides (1983)). They are also broadly consistent with model-based estimates derived from the underlying demand for housing and hedonic functions.

Historical long run rates of real house price inflation slow the estimated overall rate at which homes filter in the United States, but only by a modest amount. That is because real annualized house price inflation in the United States between 1975 and 2011 was just 0.66 percent. Regional differences do occur, however. Annualized real rates of house price inflation between 1975 and 2011 were roughly 2 percent in the North East and Pacific regions, causing filtering rates to be slower in those locations. Over that same period real house price inflation was nearly flat or even negative elsewhere in the country, causing filtering rates to be faster.

From a policy standpoint, the results in this paper suggest that for most locations, filtering rates are high enough to ensure that private markets are a viable long run source of lower income housing. This strengthens support for housing voucher-type programs in which families seek housing in the private market, and especially so in locations likely to experience flat or declining real house prices. This also suggests that investment in place-based housing construction programs like public housing and the Low Income Tax Credit (LIHTC) should target locations likely to exhibit high long term rates of house price inflation. This has not been the case, however. LIHTC tax credits, for example, are allocated across states based solely on the relative size of a state's population (e.g. Eriksen and Rosenthal (2010), Eriksen (2009)). A message for policy makers is to take more seriously the market's ability to provide lower-income housing.

To clarify these and other results, the following section outlines the core empirical strategy for the repeat income model. Section 3 describes the data while Section 4 presents results from the repeat income model. Sections 5, 6, and 7 develop extensions, while Section 8 concludes.

2. Empirical Strategy

This section lays out the core empirical strategy used to estimate the repeat income model and related filtering rates. Building off of established repeat sales models (e.g. Bailey et al (1963), Case and Shiller (1989), Case and Quigley (1991), Harding et al (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 10 years old at the time of a sale or turning over of a rental unit, the "date" of that turnover is said to be 10 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

$$Y_t = e^{\gamma_t} f(X_t; \beta_t) \ , \tag{2.1a}$$

$$Y_{t+\tau} = e^{\gamma_{t+\tau}} f(X_{t+\tau}; \beta_{t+\tau}) \ . \tag{2.1b}$$

In equation (2.1a) and (2.1b), $f(X_{t+\tau}; \beta_{t+\tau})$ is an unknown and potentially non-linear function of the age-specific characteristics of the home (X) and their shadow prices (β). The elements of X include both structural and neighborhood attributes of the home. The terms γ_t and $\gamma_{t+\tau}$ represent the influence of aging of the home and are common to all properties in the market from which the sample of homes are drawn. It is these terms that measure the age-related change in income of arriving occupants having differenced away the time invariant attributes of the house and neighborhood between the time when the home was t and $t+\tau$ years in age.

If X and β are unchanged between the time the home is t and $t + \tau$ years in age, substituting (2.1a) into (2.1b) yields,

$$Y_{t+\tau} = e^{\gamma_{t+\tau} - \gamma_t} Y_t \; . \tag{2.1c}$$

Taking logs and rearranging,

$$\log(\frac{Y_{t+\tau}}{Y_t}) = \gamma_{t+\tau} - \gamma_t + \omega_{t+\tau} \, , \tag{2.2}$$

where ω is a random error term. Provided X and β are time-invariant and, contingent on the multiplicative structure in (2.1a) and (2.1b), $f(X;\beta)$ drops out of the model. This eliminates the need to impose a specific functional form on $f(\cdot)$ and enhances the reliability of the estimated values for γ_t and $\gamma_{t+\tau}$. The percentage change in income of the arriving occupant in the home – holding constant time invariant features of the house and neighborhoods – is then captured by the difference in the constant terms from the underlying equations (2.1a) and (2.1b).

Consider now a sample of properties (*i = 1, ..., n*) that experience turnovers at various ages. For such a sample, the model in (2.2) becomes,

$$\log(\frac{Y_{t+\tau,i}}{Y_{t,i}}) = \sum_{t=1}^{\tau_i} \gamma_t D_{t,i} + \omega_{t,i} \qquad \text{for home } i = 1, \ldots, n \tag{2.3}$$

where D_t equals -1, 0 or 1 depending on whether a given property of age t turns over for the first time, is not turned over, or turns over for the second time, respectively. Note also, that the γ terms are common across all housing units, while the rest of the variables in (2.3) vary across individual homes. Equation (2.3) is analogous to the standard repeat sales specification. It is important to note that this specification does not require information on time invariant house- and neighborhood-specific attributes. Those features difference out of the model. Moreover, the vector of γ parameters can be readily estimated by regressing the log change in income for arriving occupants between turnover dates on the vector D.

The model in (2.3) implicitly assumes that (i) the coefficients β are time invariant, and (ii) the attributes of the home in X are unchanged between sale dates. Subject to these assumptions, (2.3) measures of the rate at which homes filter down – or up – as a home ages.

3. Data

3.1 Panel structure

Data for the analysis are taken from the national core files of the 1985-2009 waves of the American Housing Survey (AHS). The AHS surveys the occupants of roughly 55,000 homes every two years, following individual homes over time. This yields a panel that is unique among major surveys in that it is the homes that are followed and not the occupants. The survey is conducted every odd year (e.g. 1985, 1987 ...). Each survey contains an extensive array of questions about the house, neighborhood, and occupants. As would be expected, few homes are present throughout the entire history of the 1985-2009 panel, but instead, individual homes enter and leave the survey at different times but not in any systematic fashion.

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. This is true both for owner-occupied units and also rental units. That key feature of the data makes it feasible to estimate the repeat income models. Additional information in the AHS also allows for various extensions of the core models in addition to supplemental analyses that will be described later in the paper.[6]

3.1 Summary statistics

Summary statistics are provided in Table 1. In the top row of the table, notice that the average number of years between home turnovers is 3.96 for rental units and 6.80 for owner-occupied units. The longer time between turnovers for owner-occupied units is consistent with the well known fact that renters are especially mobile. Notice also that among the rental units, 12.1 percent experience just one pair of turnovers (or one "repeat turnover") while 56.4 percent of the units have four or more pairs of turnovers. Among the owner-occupied units, 51.7 percent experience just one pair of turnovers, while

[6] Relatively few papers have taken advantage of the panel feature of the AHS, possibly because of the extensive coding efforts required. Recent exceptions include Harding et al. (2003, 2008) and Ferreira et al (2010).

just 5.0 percent have four or more pairs of turnovers. We will draw on these multiple turnover homes in portions of the empirical work to follow.

Table 1 also reports three measures of the average log change in arriving occupant income between turnover dates. In the first, income is expressed in nominal terms, and the average log change in arriving occupant income is 6.88 percent for rental units and 15.55 percent for owner-occupied units. These values are obviously pushed upward by the general rate of inflation, masking possible filtering effects. To control for inflation, the second measure expresses income in real (year 2009) dollars. In this case, the average log change in arriving occupant income between turnover dates is negative 4.96 percent for rental units and negative 4.76 for owner-occupied units. For the third income measure, arriving occupant nominal income is deflated by average U.S. household nominal income at the time the family moves into the home.[7] For this measure, the average log change in income is negative 4.49 percent for rental units and negative 6.0 percent for owner-occupied homes.

The summary measures just described provide direct evidence that housing filters down, on average: there should no longer be debate on this point (e.g. Bond and Coulson (1990)). However, the summary measures in Table 1 do not control for the time between turnover dates, and for that reason, the precise rate at which homes filter down is still unclear. To allow for variation in turnover times, we turn now to the repeat income model described earlier.[8]

4. Estimate of filtering rates by house age

4.1 The repeat income model

I begin with Figure 1 which plots the repeat income indexes with income expressed in nominal dollars. Both in this figure and in the figures to follow, the 95 percent confidence band associated with the repeat income indexes is also plotted (based on robust standard errors, both here and in the figures to follow). Observe also that age of the housing unit is on the horizontal axis while the vertical axis

[7] Both here and later in the paper, U.S. average income is measured using data from the current population survey (CPS) as obtained from the IPUMS website (www.ipums.org).
[8] Additional summary measures in Table 1 are highlighted later in the discussion.

indicates the percentage difference in arriving-occupant income for a house of a given age in comparison to that of a newly built home.

In viewing the plots in Figure 1, it is evident that for both rental (Panel A) and owner-occupied units (Panel B), nominal income of the arriving occupant tends to increase with the age of the home. For reasons already noted, that upward tilt likely reflects the influence of inflation.

Figure 2 presents a corresponding set of plots with income of the arriving occupant expressed in year 2009 dollars. As before, indexes based on rental units are in Panel A while indexes for owner-occupied units are in Panel B. These plots have the anticipated downward slope indicating that adjusted for inflation, older homes do indeed tend to be passed down to families of lower income. As a broad characterization, the plots are also convex, implying more rapid filtering when a home is young, and slower filtering when the home is older.

Figure 3 provides analogous estimates with arriving-occupant income normalized by U.S. average income at the time the family moves into the home. The pattern repeats: as in Figure 2, the plots are downward sloping and convex reinforcing the perception that housing filters down rapidly at first but more slowly as the home ages.

4.2 Occupant satisfaction

The AHS provides an additional opportunity to infer the sense in which homes filter down as they age. The survey asks home occupants to rate their level of "satisfaction" with the housing unit on a scale of 1 (worst) to 10 (best). Subjective measures of this sort are of course subject to questions of interpretation. One occupant's sense of what it means to give a house a score of 7 may differ from that of another occupant.[9] Nevertheless, it seems likely that there is meaningful information about the quality of the home embedded in the survey responses. To the extent that is true, we would expect evaluations of

[9] In principle, occupant satisfaction should be sensitive to the degree of consumer surplus, which is sensitive to rent (price). Given the subjective nature of the survey question, however, a less precise interpretation seems warranted.

satisfaction with the home to deteriorate over time provided the flow of services from the home deteriorates with age.

Bearing the caveats above in mind, I re-estimate the repeat income model from (2.3), but use as the dependent variable the difference in levels (not logs) in arriving occupant satisfaction with the home across turnover dates. Results for owner-occupied and rental units are provided in Figure 4, Panels A and B for rental and owner-occupied units, respectively.

As is evident, arriving occupant satisfaction with the home deteriorates as the home ages. The rate of deterioration is high in the first forty years of a home's life, and slows thereafter. The rate of deterioration also appears to be faster for rental units as compared to owner-occupied units. These patterns reinforce the patterns from the repeat income models in Figures 2 and 3.[10]

The plots in Figures 2, 3, and 4 are striking and also point to further questions. For example, why are the plotted indexes convex? What determines the magnitude of the estimated rates of filtering? Are those magnitudes large enough to be important for policy and other considerations? The following sections consider these and related questions.

5. What drives the estimated rate of filtering?

5.1 Survivor effects

The downward sloping patterns in Figures 2-4 confirm that homes filter down, on average. This is consistent with the view that housing tends to deteriorate over time. In that regard, the plots clearly support the filtering hypothesis. Less straight forward is why the plotted patterns in Figures 2 and 3 are convex.

One possible explanation for the convex shape of the plots is that older homes may possess unobserved attributes that slow the rate of filtering. Previous studies, for example, have confirmed that homes tend to be demolished when they become sufficiently obsolete and/or dilapidated (McMillen and

[10] Table 1 also reports the average change in the satisfaction index between turnover dates. For rental units, the average change is negative 0.045 while for owner-occupied units the average change is negative 0.06.

O'Sullivan (2011), Brueckner and Rosenthal (2010), Rosenthal (2008), Dye and McMillen (2007), Rosenthal and Helsley (1994)). As a result, very old homes may have special features that enhance their durability and appeal, enabling such homes to retain value and delay demolition. A noteworthy example would be homes placed on the historic register. Such homes may increase in value with age because of an expanding sense of history. If older homes possess unobserved traits that slow the rate of filtering, this would contribute to the convex patterns in Figures 2 and 3.

I have two responses to this issue. The first is to recognize that few homes are demolished before age fifty or so. Moreover, the plots in Figures 2-4 tend to flatten out beginning at about age 40. The central patterns in the figures, therefore, seem likely to be robust to possible survivor effects. Second, survivor effects are grounded in the possible influence of unobserved house attributes on filtering rates. For that reason, in the discussion to follow, I estimate a series instrumental variable models that seek to address this issue directly. For these purposes, it will be convenient to focus on a restricted version of the model.

5.2 Restricted model

A restricted version of (2.3) can be estimated by constraining the rate at which homes filter down (or up) to be constant with each passing year that the home ages. While such a model does not allow for the non-linear patterns of age-related filtering evidenced in Figures 1-4, it provides other advantages that will become apparent. The model has the general form of,

$$\log\left(\frac{Y_{t+\tau,i}}{Y_{t,i}}\right) = \gamma\tau_i + \omega_{t,i} \quad \text{for observation } i = 1, \ldots, n \tag{5.1}$$

Estimates based on this specification are reported in column (1) of Tables 2 and 3 for rental and owner-occupied units, respectively. For the Panel A models in each of the tables, arriving-occupant income is expressed in constant (year 2009) dollars. For the Panel B models in each of the tables, arriving-occupant income is deflated by U.S. average income. All of these models control for MSA fixed effects with standard errors clustered at that level.[11]

Expressing income in constant dollars, the estimated rate of filtering among rental units is -1.83 percent per year (column 1 of Panel A in Table 2) while for owner-occupied units the rate of filtering is -0.40 percent per year (column 1 of Panel A in Table 3). Both estimates are highly significant. Deflating arriving-occupant income by U.S. average income (column 1 of Panel B in the tables), the corresponding estimates are higher: for rental units -2.96 percent per year, and for owner-occupied units -1.57 percent per year.

A number of robustness checks will be presented shortly. However, two features of these estimates will persist. The first is that filtering rates are higher among rental as opposed to owner-occupied units. This is consistent with previous literature which suggests that owners of rental units have less incentive to maintain their properties as compared to owner-occupiers (e.g. Henderson and Ioannides (1983)). The second is that filtering rates are higher when considering *relative* economic status as opposed to the real purchasing power of an individual's income. This is consistent with the idea that homes are occupied by the highest bidder and that prices will adjust to clear the market, or at least approximately so. This suggests that filtering rates depend not only on the rate at which house prices and rents decline with age, but also on the equilibrium matching of households into the existing mix of homes in the market (e.g. Braid (1984), Bond and Coulson (1989), Brueckner and Rosenthal (2010)). In that regard, filtering rates must also depend on housing demand. I elaborate on this idea below.

5.3 Filtering and housing demand

Consider the following simple housing demand function:

$$\log(h_{t,i}) = \theta_Y \log(Y_{t,i}) + \theta_q \log(q_{t,i}) \quad . \tag{5.2}$$

[11] In total, 146 metropolitan statistical areas (MSAs) are identified in the AHS data. All non-MSA locations are group together for a final, 147th area.

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 owner-occupied units, the price per unit of housing – on a quality adjusted basis – is then 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 rental units, q would be the quality adjusted rent. Many estimates of housing demand based on the specification in (5.2) can be found in the literature (e.g. Rosen (1979), Hoyt and Rosenthal (1990)).

Rearranging (5.2),

$$\log(Y_{t,i}) = \frac{1}{\theta_Y}\log(h_{t,i}) - \frac{\theta_q}{\theta_Y}\log(q_{t,i}) \ . \tag{5.3}$$

Then, differencing relative to the income of the arriving occupant at the following sale (or turnover in the case of rental units), the filtering regression becomes,

$$\log(\frac{Y_{t+\tau,i}}{Y_{t,i}}) = \frac{1}{\theta_Y}\log(\frac{h_{t+\tau,i}}{h_{t,i}}) - \frac{\theta_q}{\theta_Y}\log(\frac{q_{t+\tau,i}}{q_{t,i}}) + \omega_{t,i} \tag{5.4}$$

With a constant annual rate of depreciation, $\log(\frac{h_{t+\tau,i}}{h_{t,i}}) = d\tau_i$ where d is the depreciation rate. Substituting into (5.4),

$$\log(\frac{Y_{t+\tau,i}}{Y_{t,i}}) = \frac{d}{\theta_Y}\tau_i - \frac{\theta_q}{\theta_Y}\log(\frac{q_{t+\tau,i}}{q_{t,i}}) + \omega_{t,i} \tag{5.5}$$

Comparing (5.5) to (5.1), several general principles emerge that govern the rate at which homes filter down. First, an increase in the quality adjusted price (rent) holding constant the time between turnovers slows the rate at which homes are passed down to families of lower income status. This follows since $-\frac{\theta_q}{\theta_Y} > 0$ given that higher priced homes tend to be occupied by higher income families ($\theta_q < 0$) and the income elasticity of demand is positive ($\theta_Y > 0$). Second, it is evident that $\gamma = \frac{d}{\theta_Y} < 0$ since d is negative. This says that as a home ages – holding quality adjusted price (rent) constant – the rate at which the home filters down increases with the depreciation rate (*d*) while decreasing with the income elasticity of demand (θ_Y). The effect of depreciation is intuitive and standard in the filtering literature. The effect of the income elasticity of demand for housing is somewhat new despite closely related ideas in the literature and therefore warrants a bit of explanation (e.g. Bond and Coulson (1989)).

Consider a given percentage change in the quality of the home, as denoted by $d\tau_i$. How large a percentage change in occupant income must occur for the market equilibrium matching of homes and occupants implicit in the demand function in (5.2) to be met? Holding *q* constant, it is clear from (5.5) that the answer is sensitive to the income elasticity of demand for housing. If the income elasticity equaled 1, then the equilibrium level housing occupied by a given family increases in exact proportion with their income: in this instance, a change in housing services of $d\tau_i$ would be matched by an equal percentage change in occupant income, in equilibrium. If instead the income elasticity of housing demand is less than 1, then a given percentage change in housing services must be matched in equilibrium by a more than proportionate change in occupant income. This is related to arguments in Bond and Coulson (1989). They emphasize that because housing is a normal good, as the flow of services from a home declines the willingness to pay for the home declines more quickly for higher income families than for lower income households. That difference contributes to filtering as lower-income families become increasingly likely to outbid higher income households as the home deteriorates.

From (5.5) it is also clear that for any given increase in the quality adjusted rent (price) of housing, homes filter down more slowly when housing demand is more price elastic (θ_q is a larger negative value) and housing demand is less income elastic (θ_Y is a smaller positive value). This latter effect is of opposite direction from the interaction between the income elasticity and the depreciation rate (*d*), and for that reason, the overall influence of the income elasticity on filtering rates is ambiguous, a priori. In practice, however, as will be seen later in the paper, long run real house price inflation has been nearly flat outside of New England and the Pacific region. For most locations in the U.S., therefore, lower income elasticities amplify filtering rates.

Expression (5.5) has important implications for estimation of the rate of filtering. It suggests that it is desirable to control for changes in *quality adjusted* unit house prices (rents) since such changes have a direct effect on filtering rates. Moreover, if the change in house price (rent) and the time between turnover dates is correlated, then failing to control for house price (rent) could bias estimates of the rate of age-related filtering.[12] For these reasons, the next several columns of Tables 2 and 3 present models that take changes in price (rent) into account.

5.4 Allowing for price (rent)

Several issues arise when attempting to estimate (5.5). The first is how to measure $\log(q_{t+\tau,i}/q_{t,i})$ given that q represents the *quality adjusted* rent (price) of the home. A second is whether a given measure of $\log(q_{t+\tau,i}/q_{t,i})$ could be correlated with the model error term in a manner that might bias estimates of the rate at which homes filter.

As a starting point, I proxy for $\log(q_{t+\tau,i}/q_{t,i})$ using the log change in actual – not quality adjusted – sale prices (rents) for the individual homes. This is convenient but measures $\log(q_{t+\tau,i}/q_{t,i})$ with systematic error in addition to any random sources of measurement error that may occur. To clarify, let $p_{t,i}$ denote the sale price (rent) on a home while $h_{t,i}$ is the number of quality adjusted units in the home as before. Then since $p_{t,i} = q_{t,i}h_{t,i}$ and recalling the linear approximation, $\log(h_{t+\tau,i}/h_{t,i}) = d\tau_i$, the log change in actual sale price (rent) is,

$$\log(p_{t+\tau,i}/p_{t,i}) = \log(q_{t+\tau,i}/q_{t,i}) + d\tau_i \tag{5.6}$$

[12] This is related to a concern that arises when estimating repeat sales indexes. Previous studies have noted that repeat sales models are potentially subject to sample selection bias to the extent that homes that turnover more quickly exhibit unusual rates of price appreciation (e.g. Gatzlaff and Haurin (1997)).

Expression (5.6) makes clear that the log change in actual price (rent) depends on both the log change in the quality adjusted price (rent) as well as the depreciation of the housing stock between turnover dates.

Rearranging (5.6) and substituting into (5.5) gives,

$$
\begin{aligned}
\log\left(\frac{Y_{t+\tau,i}}{Y_{t,i}}\right) &= \frac{d}{\theta_Y}\tau_i - \frac{\theta_q}{\theta_Y}\left[\log\left(\frac{p_{t+\tau,i}}{p_{t,i}}\right) - d\tau_i\right] + \omega_{t,i} \\
&= \frac{d}{\theta_Y}(1+\theta_q)\tau_i - \frac{\theta_q}{\theta_Y}\left[\log\left(\frac{p_{t+\tau,i}}{p_{t,i}}\right)\right] + \omega_{t,i}
\end{aligned}
\qquad (5.7)
$$

From the second line of expression (5.7), it is evident that using actual price (rent) as a proxy for $\log(q_{t+\tau,i}/q_{t,i})$ causes the estimated rate at which homes filter with age, d/θ_Y , to be scaled by (1+ θ_q). Because previous studies typically find that θ_q is both negative and well below 1 in magnitude, this suggests that OLS estimates of (5.7) will yield downward biased estimates of the age-related rate at which homes filter.

Consider next the correlation between τ_i and $\log(p_{t+\tau,i}/p_{t,i})$. Based on the data used for Tables 2 and 3, for rental units the correlation between τ_i and the log change in rent is 4.92 percent, while for owner-occupied units the analogous correlation with respect to sale price is 7.07 percent. Because these correlation rates are low this suggests (but does not guarantee) that the correlation between τ_i and $\log(q_{t+\tau,i}/q_{t,i})$ is also likely low. That in turn implies that the estimates from column (1) of the panels in Tables 2 and 3 are likely only mildly biased, and in that sense, good approximations of the true age-related rate at which homes filter. Indirect evidence of this possibility is provided in column 2 of the tables.

Column 2 of the tables presents OLS estimates of (5.7) in which the log change in a home's actual rent (price) between turnover dates is included in the model. Notice first that the coefficient on $\log(p_{t+\tau,i}/p_{t,i})$ in each of the four panels is positive and highly significant. This is as anticipated given that θ_q < 0 and θ_Y > 0 ensure that $-\theta_q/\theta_Y > 0$.

I will examine the influence of $\log(p_{t+\tau,i}/p_{t,i})$ in detail in Section 7. For now, observe that for both panels for the rental (Table 2) and owner-occupied units (Table 3), adding the log change in rent (price) to the models has little effect on the estimated rate at which homes filter down in comparison to the corresponding estimates in column (1). This is consistent with the weak correlation between τ_i and $\log(p_{t+\tau,i}/p_{t,i})$ noted above and the possibility that the column (1) estimates are a good approximation of age-related filtering rates. Nevertheless, it is desirable to probe further.[13] Accordingly, columns (3) through (5) of the tables offer a different identification strategy that seeks to address directly possible concerns about measurement error in (5.7) and also the possibility that log price (rent) changes could be endogenous.

In columns (3) through (5), as before, all of the models include MSA fixed effects to control for time-invariant MSA attributes; the standard errors are also clustered at that level. In addition, for all of these models, I instrument for $\log(p_{t+\tau,i}/p_{t,i})$ in a GMM framework. If instruments can be found that are strongly correlated with $\log(q_{t+\tau,i}/q_{t,i})$ – the quality adjusted change in price (rent) – but not correlated with τ_i and the model error term, this would yield consistent estimates of the rate of filtering. Two sets of instruments are used for these models.

The first set of instruments are a series of dummy variables for the time period in which the home last turned over for a given pair of turnover dates: in the 1980s, 1990 to 1996, 1997 to 2005 and 2006 to 2009 (where the later is the omitted category). The period in which a home turns over would clearly affect the potential change in quality adjusted rent (price) relative to a prior turnover date since rent (price) are period-specific – this is the primary argument for instrument strength.

[13] I cannot rule out, for example, that estimates in columns (1) and (2) may be similar because they suffer from a similar degree of bias but from different sources. For column (1) of each panel, if τ_i and $\log(q_{t+\tau,i}/q_{t,i})$ are positively correlated, then omitting $\log(q_{t+\tau,i}/q_{t,i})$ should yield downward biased estimates of the magnitude of the rate of filtering. For column (2) of each panel, the estimated coefficient on τ_i is scaled by $(1+\theta_q)$ as shown in (5.7), and this also biases the magnitude of the filtering rate downward with $\theta_q < 0$.

The second instrument is the change in an aggregate-level quality adjusted house price index between turnover dates. To form this instrument I merged annual house price index values obtained from the Federal Housing and Finance Agency (FHFA) into the AHS data.[14] The indexes used were the FHFA home purchase repeat sales house price index. For housing units in MSAs (metropolitan statistical areas) identified in the AHS, MSA-level price indexes were used. For housing units not in MSAs identified in the AHS, the FHFA national-level house price index was used. These indexes should also be strongly correlated with $\log(q_{t+\tau,i}/q_{t,i})$ given the repeat sales design used by the FHFA in creating the index values.

Several features of the instruments help to ensure that they are exogenous and also not correlated with τ_i. It should be emphasized that both sets of instruments capture aggregate-level (MSA or US-wide) changes in economic conditions. For that reason, they should be independent of neighborhood-level and/or house-specific shocks that affect the desirability of a given home. The weak correlation between τ_i and $\log(p_{t+\tau,i}/p_{t,i})$ noted above also helps to ensure that the instruments are not correlated with τ_i. This is especially so for the period-dummy variables which are specified in periods of roughly six years in length. As noted earlier, summary measures in Table 1 indicate that most household move within six years. Because household moves are so often driven by changes in life cycle conditions (e.g. changes in family size, marital status, employment, etc.), the six-year instrument window reduces the potential influence of strategic moves that are timed to take advantage of a given's year's house price level.[15]

The primary reason to be cautious of the instruments is that income is a driver of housing demand and may therefore affect price. Although measuring income at the individual level helps to mitigate this concern, I cannot rule out the possibility that macroeconomic shocks could still affect the change in both individual occupant income and the FHFA price index between turnover dates. This could cause the FHFA price index to be correlated with the model error term. The period-dummy instruments seem likely

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

[15] I also estimated GMM models including calendar year dummy variables for the second turnover date directly in the repeat-income regression and retaining the FHFA price index as the only instrument. Results were similar to the GMM estimates in Tables 2 and 3 and are not reported for that reason.

to be less sensitive to this concern for reasons noted above (i.e. that life-cycle factors likely dominate household move decisions over a six-year span). Moreover, for both instruments, these concerns are further reduced when occupant income is normalized relative to U.S. average income since this implicitly differences away aggregate shocks that affect both aggregate – and individual – income.

Turning to the results, in Tables 2 and 3, only the period-dummy instruments are used in column (3) while only the FHFA instrument is used in column (4). In column (5) both sets of instruments are included in the models. The complete first-stage regressions are provided in the appendix and correspond to anticipated patterns. In particular, the period dummy variables are generally significant and the FHFA price index is a strong, positive predictor of the change in rent and price between turnover dates for both the rental and owner-occupied samples.

Coefficient patterns and diagnostic statistics presented at the bottom of each panel in Tables 2 and 3 provide further support for the instruments and also some caveats. In all cases the instruments appear to be strongly correlated with the rent (price) change variable, and especially so for the owner-occupied units. The Kleibergen-Paap weak instrument F-Statistic takes on values from roughly 13.5 to 220, with stronger values when only the FHFA index is used. This suggests that weak instrument bias is not a concern (e.g. Stock and Yogo (2005)).

Evidence based on the Hansen-J over-identification tests is available only for columns (3) and (5) which are overidentified. For rental units (Table 2), the p-values when occupant income is expressed in real terms (Panel A) are 0.29 and 0.17 in columns (3) and (5), respectively, and 0.58 and 0.10 when income is expressed relative to U.S. average income (Panel B). For owner-occupied units the corresponding p-values are high when income is expressed in real terms, 0.93 and 0.68, but just 0.08 when income is expressed relative to U.S. average income. Limitations of overidentification tests are known, including weak power and a tendency for false positives and false negatives. Nevertheless, the mixed patterns just noted suggest that some caution should be used when considering the possible validity of the instruments.

A further indirect test of the validity of the instruments is obtained by comparing the coefficient estimates from columns (3), (4), and (5). Provided that both sets of instruments are valid and strong, then estimates from all three columns should be similar. Looking across columns in the different panels, it is evident that the rent (price) coefficients are similar when occupant income is measured in real terms (Panel A) for both rental and owner-occupied units. When occupant income is measured relative to U.S. average income (Panel B), the rent (price) coefficients are sensitive to the model specification for rental units (Table 2) but are mostly robust for the owner-occupied sector (Table 3). Overall, these results are encouraging.

Consider now the age-related filtering rates implied by the GMM estimates from the two tables and focus first on the Panel A models in which occupant income is expressed in real terms. Observe that the GMM estimates of the rate of filtering are somewhat larger in magnitude than in columns (1) and (2): for rental units, the estimated filtering rate increases from roughly -0.02 to roughly -0.025, while for owner-occupied units the filtering rate increases from -0.004 to between -0.005 and -0.007 depending on which GMM estimate is used. The increase in filtering rates with the GMM specification is as anticipated and provides support for the validity of the instruments. It should also be noted that the increase in filtering rates with the GMM specification is modest, consistent with arguments above that the models in columns (1) and (2) are likely reasonable approximations of age-related filtering.

Consider next the Panel B models for which occupant income is expressed relative to U.S. average income. Once again, the GMM estimates are, for the most part, similar to the OLS estimates in columns (1) and (2). This further reinforces the sense that the estimated rates of age-related filtering in Tables 2 and 3 are robust to the different model specifications.[16]

[16] It is worth noting that when occupant income is measured relative to U.S. aggregate income in Panel B of both Tables 2 and 3, the coefficient on the log change in rent (price) is much lower in magnitude (and of opposite sign) in comparison to the other GMM models. Apart from those estimates (in column (3) of Panel B), the GMM estimates of the coefficients on the log change in rent (price) are considerably larger than the corresponding OLS values in column (2). This suggests that either the change in rent (price) between turnover dates is negatively correlated with the model error term, or that the instruments control for classical measurement and thereby offset attenuation bias.

5.5 Unobserved house attributes

This section revisits the possibility that older homes may be of a more durable type of construction and/or less prone to obsolescence than the norm. This was offered as a possible explanation for the flattening out of the filtering rate among older homes in Figures 2 through 4. To motivate, suppose that homes are made of either brick or wood, and that brick homes are more durable, slowing the rate of filtering. If construction type is intrinsically valued by households, then with construction type represented by X, (2.1) can be re-written as:

$$Y_{t,i} = e^{\gamma_t + bX_i} f(X_i;\beta) \ . \tag{5.8}$$

In (5.8), the structural attributes affect the income of the arriving occupant through the f function as before but also by influencing directly the rate at which the home filters down. Manipulating (5.8) as with the model earlier in the paper, the analogue to (5.5) becomes,

$$\log(\frac{Y_{t+\tau,i}}{Y_{t,i}}) = \frac{d}{\theta_Y}\tau_i - \frac{\theta_q}{\theta_Y}\log(\frac{q_{t+\tau,i}}{q_{t,i}}) + \lambda_i + \omega_{t,i} \tag{5.9}$$

where $\lambda_i = bX_i$.

Expression (5.9) suggests that an effective solution to possible concerns about unobserved house attributes that might affect filtering rates is to include house fixed effects in the model, λ_i. Column (6) of panels A and B in Tables 2 and 3 does just that, drawing on the multiple turnover pairs described in Table 1. As above, these models are estimated by GMM using both sets of instruments in the first stage rent (price) equation.

Consider the rental sector first (Table 2). Note that there are 11,624 house fixed effects for 43,175 repeat-rent observations. The smaller number of observations relative to earlier models arises because homes with only one turnover pair are dropped from the sample. When income is expressed in real terms (Panel A of Table 2) the estimated filtering rate is -0.0311, somewhat higher than the corresponding estimate of -0.025 in column (5) for which MSA fixed effects are used. When income is deflated by U.S. average income, the filtering rate is -0.0416, also larger in magnitude than the MSA fixed effect estimate in column (5). Both estimates are also highly significant. Moreover, the higher estimated coefficients supports the view that house fixed effects help to control for survivor bias arising from unobserved house attributes.

This procedure works less well for owner-occupied units because there are too few multiple turnover-pairs in the sample (note that there are 2,452 house fixed effects for just 5,680 repeat sale observations). This reduces the power to identify the coefficients, and consistent with that view, I am unable to identify a filtering effect in column (6) of Panel A when income is expressed in real terms. For Panel B, with income deflated by U.S. average income, the estimated filtering rate is significant and similar to the MSA fixed effect estimate in column (5).

6. Additional structure: Depreciation and the income elasticity of demand

6.1 Overview

This section develops a more conceptually based estimate of the rate at which homes filter as they age holding quality adjusted house rents and prices constant. I do this by separately estimating house depreciation rates and the income elasticity of demand for housing. Those estimates are then used to form d/θ_Y directly.

6.2 Depreciation

I begin with house rent and price hedonic models used to estimate depreciation rates. These models are presented in Table 4. In each case, the dependent variable is the log of the house rent (price) in constant (year 2009) dollars. Control variables include the age of the home in years, the number of rooms, number of bathrooms, whether the home is single family detached, single family attached, or multi-family (the omitted category).[17] Also included are MSA and year fixed effects to allow for changes in rent (price) levels across years and MSAs.

[17] Summary measures for the dependent variables and the control measures are in Table 1. Owner-occupied homes are larger (5.91 rooms versus 4 for rental units), have more bathrooms (1.61 versus 1.13), and are much more likely

Consider now the estimates in Table 4. Notice that the coefficient on the age of the home is -0.003 for the rental units and -0.007 for the owner-occupied units (both of which are highly significant). These estimates indicate that, controlling for other house attributes, on average house rent and price decline by 0.3 and 0.7 percent per year as the home ages. For the owner-occupied units, the rate of depreciation is close to the rate of filtering when income is expressed in real dollars as discussed above, but well below filtering rates based on occupant income relative to U.S. average income. For the rental units, the estimated rate of depreciation is also well below the rate of income filtering regardless of whether income is measured in 2009 real dollars, or relative to U.S. average income. On balance, these estimates of house rent (value) depreciation are much lower than the estimated filtering rates but that is plausible. As discussed earlier, the rate at which homes filter down to lower income families is amplified when the income elasticity of demand for housing is less than 1.

6.3 Income elasticity of demand for housing

Most estimates of the income elasticity of demand for housing in the literature suggest that housing demand is quite income inelastic, with elasticities well below 1 (e.g. Rosen (1979), Hoyt and Rosenthal (1990), Rosenthal, Duca and Gabriel (1991)). To explore this issue further, Table 5 presents estimates of housing demand models for the rental and owner-occupied sectors based on the specification outlined in expression (5.2). The dependent variables are the log of gross rent and the log of purchase price in year 2009 dollars. Control variables include the log of family income in year 2009 dollars, marital status, presence of school age children, race, and education of the household head. Quality adjusted house rent (price) are captured by MSA and year fixed effects: the assumption here is that local rents (price) are common to a given MSA, adjusted for the general price level throughout the economy in that year.[18]

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to be single family detached (74.5 percent versus 22.3 percent). Owner-occupied homes are also somewhat younger (25.7 years versus 35.22 years).

[18] Summary measures for the dependent variables and also the control variables are provided in Table 1. Owner-occupiers have higher incomes than renters ($56,754 versus $26,291 in 2009 dollars, on average), are more likely to

The estimated income elasticities in Table 5 are 13.4 percent for renters and 41.1 percent for owner-occupiers (these estimates are also highly significant). It should be noted that these estimates do not control for the possibility of endogenous selection of individuals into rental or owner-occupied units. Nevertheless, for purposes of this paper, the estimates in Table 5 confirm that the income elasticity of demand for housing is well below 1, as in previous literature.[19]

6.4 Model based estimates of age-related filtering rates

We arrive now at the resolution of a puzzle that has contributed to confusion in policy debates about the viability of filtering and the private sector as a long-run source of lower-income housing. Most low-income families who are not in public or LIHTC housing live in old homes. But most hedonic studies including estimates in Table 4 find that the rate at which rents and house prices depreciate with age of the home is low. Because the private market builds little new unsubsidized low-income housing (e.g. Baer (1986)), how is this possible? The answer is provided, at least in part, in the structure implied by expression (5.5): income elasticities of demand for housing below one amplify the rate of filtering as the home depreciates..

To make this idea more explicit, it is revealing to divide the estimate for *d* from Table 4 by the estimate for θ_Y from Table 5. The implied annual rates of filtering are -2.48 percent for rental units and -1.80 percent for owner-occupied units. One should view these estimates with some caution, of course, as the structure in (5.5) is based on the specific assumed form of the demand function in (5.2) and the implied underlying utility function. It is also worth emphasizing that all dollar valued variables in Tables 4 and 5 are in real (year 2009) dollars. The structure-based estimates of filtering just noted, therefore, refer to filtering with arriving occupant income expressed in real (year 2009) dollars.

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be married (65.9 percent versus 33.2 percent) and are older (40.65 versus 34.48 years. Owners also are much more likely to be white (82.6 percent versus 65.9 percent) and college educated (34.8 percent versus 21.5 percent).

[19] The estimates above allow for variation in rent (price) only through the location and year fixed effects. Some previous studies based on owner-occupiers have instead drawn on favorable tax treatment of homeownership in conjunction with differences in tax rates across households as a way of generating cross-sectional variation in housing costs (e.g. Rosen (1979), Hoyt and Rosenthal (1990), Rosenthal et al. (1991)).

Bearing these points in mind, I offer two observations on the structurally based estimates of age-related filtering. First, for the rental units, they are close to the reduced form estimates noted above when occupant income is in constant (year 2009) dollars, although for owner-occupied housing they are larger (-1.8 versus -0.5 percent). Second, the structure-based estimates also indicate that filtering rates are higher among rental units.

7. House rent (price) inflation and filtering rates

The model in (5.3) makes clear that homes filter to different income groups both in response to age-related depreciation and also because of changes in quality adjusted rent (price). This section presents a set of simulations that highlight the magnitude of the latter effect.

Figure 5a presents plots of the FHFA home purchase price index for the Phoenix, Houston, and Cleveland metropolitan areas for the period 1991-2011, adjusted for inflation using the CPI-U. The three metro areas displayed were chosen for illustrative purposes. As a sun-belt location, Phoenix has grown dramatically since the early 1990s, and also experienced a dramatic boom and bust in house prices between 2000 and 2011. Houston has also grown since the early 1990s, but in this case prices have moved up at a modest and relatively steady pace throughout the period. As a rust belt city, Cleveland has lost population in recent years, contributing to a contraction in housing demand and declining prices.

Figures 5b and 5c simulate the rates at which a typical rental and owner-occupied home would filter down over the 1991-2011 period, respectively. In all cases, initial income values in 1991 were normalized to 100. For both the rental and owner-occupied sectors, I simulated the quarterly change in arriving occupant income using coefficients from Tables 2 and 3, respectively, for the GMM MSA fixed effect models in column (5) of Panel A, and adjusting the coefficients to a quarterly frequency. Recall that for the Panel A models, occupant income is expressed in real terms.

I proxy for the quarterly log change in quality adjusted rent by adding together two components. The first component is the trend rate of change in the FHFA price indexes from Figure 5a based on the overall change in the index values from 1991 and 2011 divided by the number of quarters from 1991 to

2011. This is based on the assumption that changes in real estate values are driven by changes in rents, consistent with the view that markets are efficient in the long run (e.g. Meese and Wallace (1994)). The second component is the change in the deviation from trend in a given quarter multiplied by 0.2. The scale factor 0.2 is used to reflect the assumption that rental rates are less subject to short-run volatility relative to home purchase prices .[20] Analogous simulations were developed for the owner-occupied sector (Figure 5c); in this instance, the deviation from the trend rate of change was not scaled so that the two components sum to the actual change in the FHFA index value from one quarter to the next.

Several patterns in Figures 5b and 5c are worth highlighting. First, as before, it is evident that rental units filter down at a faster rate than do owner-occupied units. Second, the price paths from Figure 5a are mirrored in the projected rates at which homes filter down – and up – in Figures 5b and 5c. These patterns highlight that short-run differences in house price inflation contribute to short-term differences in filtering rates. Third, over the two-decade period shown, real house price inflation in Figure 5a is modest for all three metropolitan areas. This implies that (i) house price (rent) inflation had relatively little effect on long run rates of filtering in the three metropolitan areas displayed, and (ii) age-related depreciation of the housing stock is the primary long run driver of filtering in these figures.

Table 6 explores this last point further for the U.S. overall and for the nine census divisions. For each area, filtering rates are decomposed into contributions from house age-related depreciation and quality adjusted house price inflation effects. In all cases, estimates are calculated in a manner analogous to the simulations in Figure 5 with one important exception: filtering rates are based on annualized rates of house price inflation from 1975 to 2011 and, in that sense, ignore short run patterns.

Based on FHFA price indexes from 1975 to 2011, the annualized real rate of house price inflation (column (1)) ranged from a high of just over 2 percent in the New England and Pacific divisions, to a low of roughly zero in several other divisions around the country. At the national level, the annualized real rate of house price inflation was just 0.66 percent over the 1975-2011 period.

[20] Changing the scale factor affects the amplitude of the patterns in Panel B but not the qualitative features of those patterns. As constructed, the deviation from trend is zero in the last quarter.

For the nation overall, in the owner-occupied sector real house price inflation appears to have slowed the overall rate of filtering by roughly 0.1 percent per year (column (5)), reducing the magnitude of the filtering rate from the 0.48 percent per year to 0.38 percent per year. In the rental sector, house price (rent) inflation slowed the rate of filtering by 0.61 percent per year (column (2)), lowering the filtering rate from 2.52 percent to 1.91 percent per year. It is also evident that filtering rates are noticeably lower in the New England and Pacific divisions because of the higher rates of house price inflation in those areas: in the rental sector, the corresponding filtering rates in the two divisions are -0.65 percent per year and -0.45 percent per year, respectively. In all other parts of the country, rental housing filtering rates are faster, as with the East South Central division for which the filtering rate is -2.58 percent per year.

8. 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 estimates of low rates of house price depreciation have contributed to doubts about the viability of private markets and filtering as a long run source of lower income housing (e.g. Margolis (1982), Bond and Coulson (1990)). This has also likely contributed to misplaced housing assistance policies, including the construction of subsidized lower-income housing in areas where filtering rates have been high (e.g. much of the interior portion of the country). This paper 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. Findings indicate that when occupant income is measured in real (constant dollar) terms – and in the absence of real house price inflation – rental housing filters down at an average annual rate of roughly 2.5 to 3 percent per year as a home ages. For owner-occupied homes, the corresponding rate is 0.5 percent per year. To put this in perspective, based on filtering rates of 2.5 percent and 0.5 percent per year, homes would filter down 72 percent and 22 percent, respectively, over a fifty year horizon. Moreover, filtering rates are faster when occupant income is measured relative to U.S. average income, and as housing becomes more income inelastic. These findings suggest that filtering is a viable long run source of lower-income housing, and especially so given that rental housing is the traditional home of the poor.

Findings also demonstrate that filtering rates vary inversely with the real rate of house price (rent) inflation, and therefore, differ across locations. For the U.S. overall, between 1975 and 2011, the real annual rate of house price inflation was 0.66 percent. At that rate of inflation, filtering rates are only slightly slower than those highlighted above. In the New England and Pacific regions, the corresponding real rate of house price inflation was roughly 2 percent per year (over the 1975-2011 period). At that rate of inflation, owner-occupied housing would have filtered down at just 0.15 percent per year, or 7.5 percent over a fifty year horizon. Such a low rate would seem to provide support for skeptics of the filtering process. However, in the rental sector, even with a 2 percent real annual rate of house price (and rent) inflation, homes would still filter down at roughly 0.5 percent per year (or 22 percent over a fifty year horizon). Moreover, outside of the New England and Pacific regions, the real annualized rate of house price inflation was close to zero over the 1975-2011 period. In these locations, filtering rates are notably higher as highlighted above.

For housing assistance advocates several messages follow. First, policy makers should take seriously the market's ability to generate lower income housing, and especially in the rental sector of the market. Second, to the extent that long run rates of house price inflation differ across locations, filtering rates will differ as well and this can have sharp implications for the desired form of housing assistance at the local level. As an example, LIHTC tax credits for low income housing construction are allocated across states based solely on the relative size of a state's population (e.g. Eriksen and Rosenthal (2010), Eriksen (2008)).[21] Such a one-size-fits-all allocation mechanism does little to recognize notable differences in filtering rates across regions. Shrinking areas like Cleveland and the rust belt, for example, have experienced sharply falling real house prices (e.g. Glaeser and Gyourko (2005)) and have even

[21]Eriksen and Rosenthal (2010) show that within states, state housing authorities partly mirror the federal allocation scheme by disproportionately reallocating LIHTC credits to the most populous metropolitan areas, on average.

chosen to bulldoze portions of their underutilized housing stock (e.g. Donvan (2009), Snyder (2010)). It is difficult to justify subsidizing construction in such locations where filtering is so robust.

More generally, historical data back to 1975 suggest that long run real house price inflation has been close to zero in most parts of the country outside of the New England and the Pacific regions. Presumably this is because of extensive opportunities to develop open land and/or to redevelop existing developments to a higher density. If that pattern persists – as seems likely in most areas – then filtering will continue to be a viable source of lower-income housing over the next several decades in most parts of the country. This weakens arguments for place-based subsidized construction programs like LIHTC, and instead points to voucher type programs as a preferred vehicle for providing housing assistance.

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Table 1: Summary Statistics

	Renter Occupied	Owner Occupied
Years between turnovers[a]	3.96	6.80
Percent 1 pair of turnovers[a]	12.12	51.74
Percent 2 pairs of turnovers[a]	14.86	30.89
Percent 3 pairs of turnovers[a]	16.58	12.40
Percent 4 or more pairs of turnovers[a]	56.44	5.0
Rent (monthly) in $2009[b]	747.07	-
Price in $2009[b]	-	191,183
Log change in nominal income between turnovers[a]	0.0688	0.1555
Log change in real income between turnovers ($2009) [a]	-0.0496	-0.0476
Log change in income relative to USA avg. between turnovers[a]	-0.0900	-0.1208
Change in occupant satisfaction index between turnovers[a]	-0.0449	-0.060
Age of house in years[b]	35.22	25.70
Number of rooms[b]	4.00	5.91
Number of bathrooms[b]	1.13	1.61
Single Family Detached[b]	0.223	0.745
Single Family Attached[b]	0.030	0.061
Family income ($2009) [c]	26,291	56,754
Age (household head) [c]	34.48	40.65
Married [c]	0.332	0.659
Single female (household head) [c]	0.374	0.177
School age children present [c]	0.254	0.322
White (household head) [c]	0.659	0.826
Black (household head) [c]	0.149	0.055
College degree or more (household head) [c]	0.215	0.348

[a]Estimates are based on the repeat income sample used in Tables 2 and 3.
[b]Estimates are based on the samples used for the hedonic regressions in Table 4.
[c]Estimates are based on the samples used for the housing demand functions in Table 5.

Table 2: Restricted Models – Renter-Occupied Units[a]
(t-stats are reported in parenthesis using robust standard errors)

Panel A: Log Change in Arriving Occupant Real ($2009) Income

	OLS		GMM With Change in Rent Endogenous			
					Inst. with Time Period FE and FHFA Price Index	
	Without Change in Rent	With Change in Rent	Inst. with Time Period FE	Inst. with FHFA Price Index	MSA Fixed Effects	House Fixed Effects
	(1)	(2)	(3)[a]	(4)[b]	(5)	(6)
Years Between Turnover (d/θ_Y)	-0.01831	-0.01972	-0.02882	-0.0247	-0.02523	-0.0311
	(-7.45)	(-8.48)	(-7.51)	(-8.65)	(-9.62)	(-9.08)
Log change in rent (θ_q/θ_Y)	-	0.19190	1.4114	0.8727	0.92504	0.8588
	-	(13.06)	(3.22)	(3.00)	(3.77)	(2.94)
MSA Fixed Effects	147	147	147	147	147	-
House Fixed Effects	-	-	-	-	-	11,624
KP Weak Inst. F-Statistic	-	-	13.82	76.41	27.76	21.63
Hansen J Over ID P-Value	-	-	0.0293	-	0.0168	0.0232
Observations	49,128	49,128	49,128	49,128	49,128	43,175
Within R-Sq	0.0021	0.0080	-	-	-	-
Root MSE	-	-	1.431	1.283	1.295	-1.421

Panel B: Log Change in Arriving Occupant Income Deflated by U.S. Average Income

	OLS		GMM With Change in Rent Endogenous			
					Inst. with Time Period FE and FHFA Price Index	
	Without Change in Rent	With Change in Rent	Inst. with Time Period FE	Inst. with FHFA Price Index	MSA Fixed Effects	House Fixed Effects
	(1)	(2)	(3)[a]	(4)[b]	(5)	(6)
Years Between Turnover (d/θ_Y)	-0.02957	-0.03097	-0.02917	-0.0374	-0.03468	-0.0416
	(-12.19)	(-13.44)	(-8.33)	(-12.77)	(-13.59)	(-12.37)
Log change in rent (θ_q/θ_Y)	-	0.18883	-0.05304	1.0652	0.68524	0.70717
	-	(13.52)	(-0.13)	(3.59)	(2.86)	(2.46)
MSA Fixed Effects	147	147	147	147	147	-
House Fixed Effects	-	-	-	-	-	11,624
KP Weak Inst. F-Statistic	-	-	13.82	76.41	27.76	21.63
Hansen J Over ID P-Value	-	-	0.5789	-	0.1042	0.7862
Observations	49,128	49,128	49,128	49,128	49,128	43,175
Within R-Sq	0.0055	0.0112	-	-	-	-
Root MSE	-	-	1.251	1.311	1.260	1.402

[a] Instruments denote whether the latest turnover was in the 1980s, 1990 to 1996, 1997 to 2005, or 2006 to 2009.
[b] Instrument is the change in the FHFA house price index between turnover dates.

Table 3: Restricted Models – Owner-Occupied Units[a]
(t-stats are reported in parenthesis using robust standard errors)

Panel A: Log Change in Arriving Occupant Real ($2009) Income

	OLS		GMM With Change in Price Endogenous			
					Inst. with Time Period FE and FHFA Price Index	
	Without Change in Price	With Change in Price	Inst. with Time Period FE	Inst. with FHFA Price Index	MSA Fixed Effects	House Fixed Effects
	(1)	(2)	(3)[a]	(4)[b]	(5)	(6)
Years Between Turnover (d/θ_Y)	-0.00406	-0.00402	-0.00710	-0.00486	-0.00480	-0.00126
	(-2.47)	(-2.69)	(-2.22)	(-1.91)	(-1.94)	(-0.25)
Log change in price (θ_q/θ_Y)	-	0.08258	0.28212	0.13839	0.15032	0.33047
	-	(6.33)	(2.08)	(1.70)	(2.09)	(2.01)
MSA Fixed Effects	147	147	144	144	144	-
House Fixed Effects	-	-	-	-	-	2,452
KP Weak Inst. F-Statistic	-	-	29.65	220.7	67.27	12.35
Hansen J Over ID P-Value	-	-	0.9301	-	0.6843	0.0922
Observations	12,263	11,757	11,754	11,754	11,754	5,680
Within R-Sq	0.0003	0.0051	-	-	-	-
Root MSE	-	-	1.019	1.007	1.007	1.137

Panel B: Log Change in Arriving Occupant Income Deflated by U.S. Average Income

	OLS		GMM With Change in Price Endogenous			
					Inst. with Time Period FE and FHFA Price Index	
	Without Change in Price	With Change in Price	Inst. with Time Period FE	Inst. with FHFA Price Index	MSA Fixed Effects	House Fixed Effects
	(1)	(2)	(3)[a]	(4)[b]	(5)	(6)
Years Between Turnover (d/θ_Y)	-0.01571	-0.01568	-0.01356	-0.01723	-0.01601	-0.01444
	(-9.68)	(-10.56)	(-4.23)	(-6.78)	(-6.46)	(-2.97)
Log change in price (θ_q/θ_Y)	-	0.08098	-0.05199	0.18411	0.08931	0.18298
	-	(6.26)	(-0.38)	(2.25)	(1.24)	(1.13)
MSA Fixed Effects	147	147	144	144	144	-
House Fixed Effects	-	-	-	-	-	2,452
KP Weak Inst. F-Statistic	-	-	29.652	220.7	67.268	12.35
Hansen J Over ID P-Value	-	-	0.0815	-	0.0850	0.0044
Observations	12,263	11,757	11,754	11,754	11,754	5,680
Within R-Sq	0.0048	0.0088	-	-	-	-
Root MSE	-	-	1.012	1.009	1.006	1.118

[a] Instruments denote whether the latest turnover was in the 1980s, 1990 to 1996, 1997 to 2005, or 2006 to 2009.
[b] Instrument is the change in the FHFA house price index between turnover dates.

Table 4: Hedonic Regressions of House Rent and Price[a]
(t-stats are reported in parenthesis using robust standard errors)

	Renter Occupied (Dependent Variable is Log of Rent)	Owner Occupied (Dependent Variable is Log of Price)
Age of house in years (*d*)	-0.00333	-0.00727
	(-16.19)	(-8.93)
Number of rooms	0.07001	0.13178
	(11.33)	(18.84)
Number of bathrooms	0.23479	0.32082
	(14.18)	(16.38)
Single Family Detached	0.01988	0.77498
	(1.09)	(5.28)
Single Family Attached	0.04241	0.44980
	(0.79)	(2.39)
MSA Fixed Effects	147	147
Year Fixed Effects	25	25
Observations	95,445	55,456
R-Sq within	0.1089	0.2874
R-Sq between	0.0239	0.0482
R-Sq overall	0.0773	0.2696

Table 5: Housing Demand Regressions[a]
(t-stats are reported in parenthesis using robust standard errors)

	Renter Occupied	Owner Occupied
Log family income (θ_Y)	0.13419	0.40471
	(55.12)	(41.97)
Age (household head)	-0.00108	0.00548
	(-6.42)	(9.83)
Married	0.05635	0.20689
	(9.15)	(9.48)
Single female (household head)	0.00852	0.08687
	(1.45)	(3.27)
School age children present	0.06634	0.07592
	(11.66)	(4.42)
White (household head)	0.07412	0.08309
	(11.29)	(3.30)
Black (household head)	-0.10711	-0.05993
	(-12.68)	(-1.49)
College degree or more (household head)	0.17424	0.43716
	(29.31)	(25.71)
MSA Fixed Effects	147	147
Year Fixed Effects	25	25
Observations	46,680	16,591
R-Sq within	0.1394	0.2213
R-Sq between	0.4578	0.4564
R-Sq overall	0.1475	0.2501

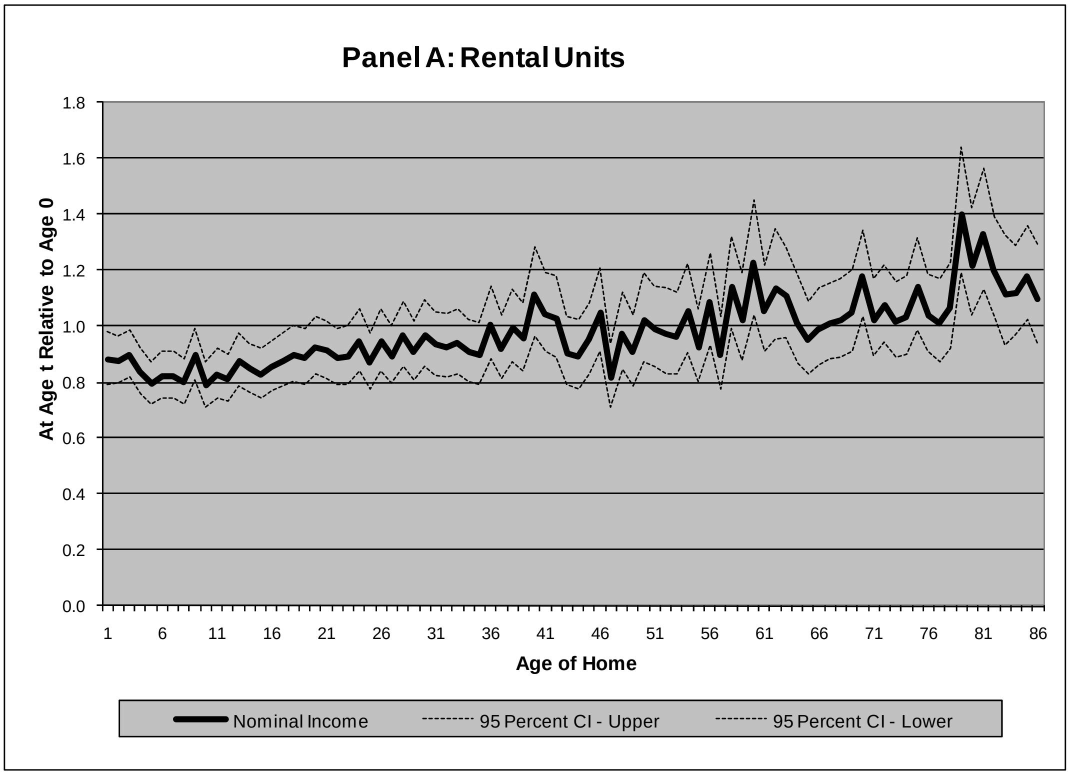
[a]Dependent variables are log of rent and log of purchase price for rental and owner units, respectively.

Table 6: Decomposing Real Income Filtering Rates into Price and Age-Related Effects (Annualized Rates Based on FHFA Real HPI Values, 1975-2011 and Model (5), Panel A Estimates from Tables 2 and 3)

		Rental Units			Owner-Occupied Units		
	Annualized Real Percent Change in the FHFA HPI 1975-2011[a] (1)	Annualized Effect on Filtering Rates From the Change in the FHFA HPI 1975-2011[b] (2)	Annual Age-Related Filtering Rate[c] (3)	Total Annual Average Filtering Rate in percent 1975-2011 (4)	Annualized Effect on Filtering Rates From the Change in the FHFA HPI 1975-2011[b] (5)	Annual Age-Related Filtering Rate[c] ((6)	Total Annual Average Filtering Rate in percent 1975-2011 (7)
USA	0.66	0.61	-2.52	-1.91	0.10	-0.48	-0.38
New England	2.02	1.87	-2.52	-0.65	0.30	-0.48	-0.18
Middle Atlantic	1.26	1.16	-2.52	-1.36	0.19	-0.48	-0.29
South Atlantic	0.35	0.32	-2.52	-2.20	0.05	-0.48	-0.43
East South Central	-0.07	-0.06	-2.52	-2.58	-0.01	-0.48	-0.49
East North Central	0.02	0.01	-2.52	-2.51	0.00	-0.48	-0.48
West South Central	-0.08	-0.07	-2.52	-2.59	-0.01	-0.48	-0.49
West North Central	0.21	0.20	-2.52	-2.32	0.03	-0.48	-0.45
Mountain	0.46	0.42	-2.52	-2.10	0.07	-0.48	-0.41
Pacific	2.24	2.07	-2.52	-0.45	0.34	-0.48	-0.14

[a]Based on the FHFA all transactions (home purchase plus refinance appraisals) index.
[b]Obtained by multiplying Col (1) by 0.92504 from Col (5), Panel A, Table 2 for rental units, and 0.15032 from Col (5), Panel A, Table 3 for owner-occupied units.
[c]From Col (5), Panel A, Table 2 for rental units, and Col (5), Panel A, Table 3 for owner-occupied units. Values are multiplied by 100.

Figure 1
Repeat Income Indexes
Nominal Income



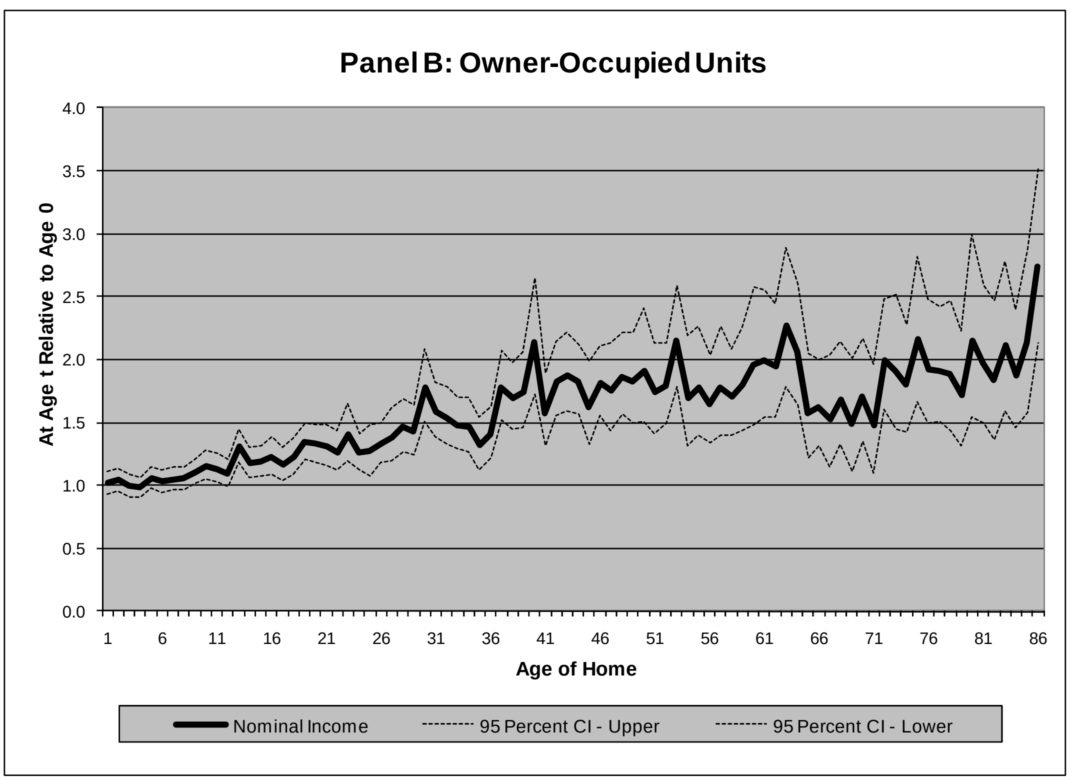


Figure 2
Repeat Income Indexes
Income Adjusted for Inflation to Year 2009 Dollars

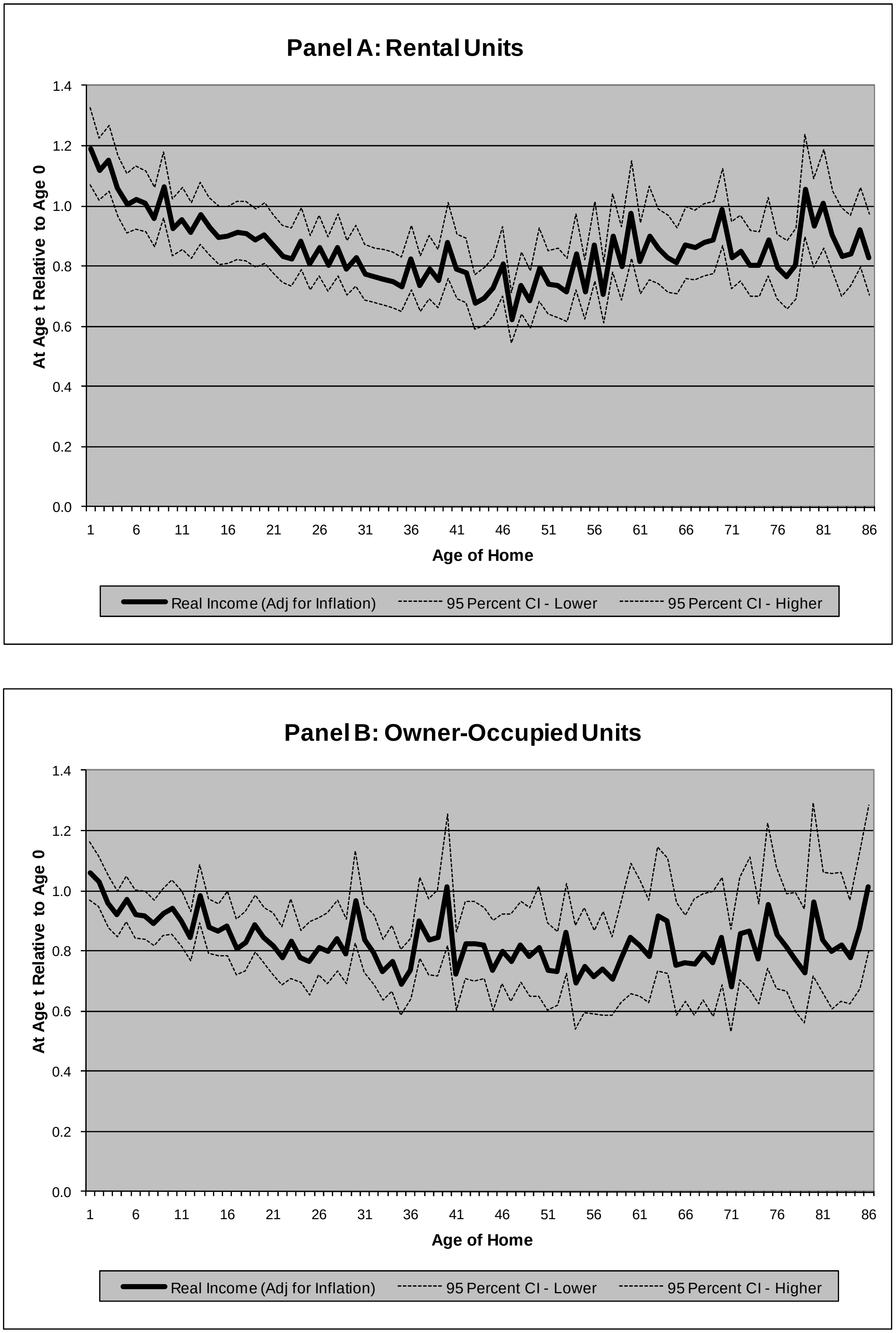
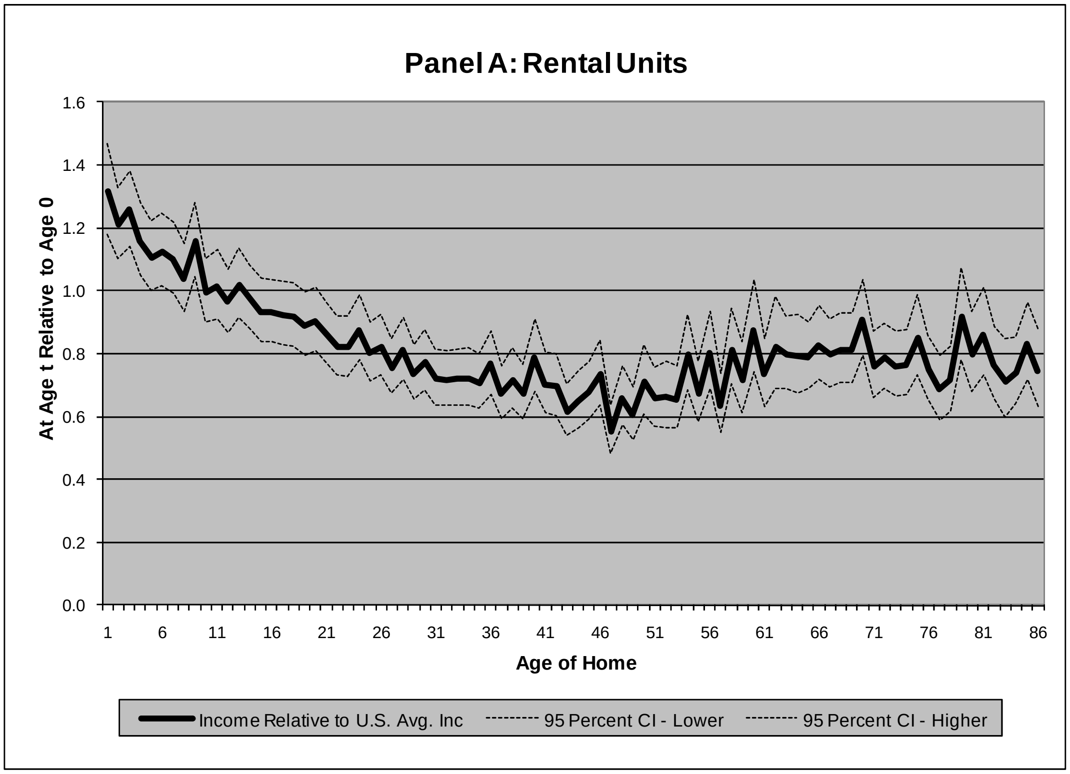


Figure 3
Repeat Income Indexes
Income Deflated by U.S. Average Income



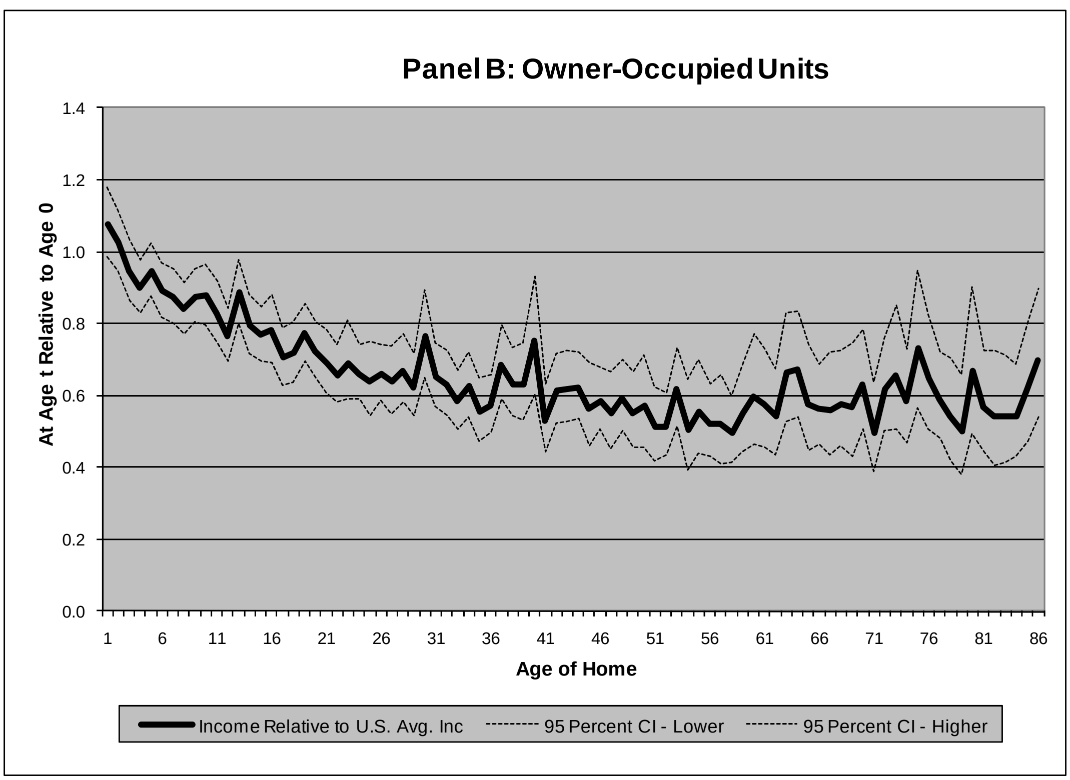


Figure 4
Repeat House Evaluation Indexes
1 is worst and 10 is best

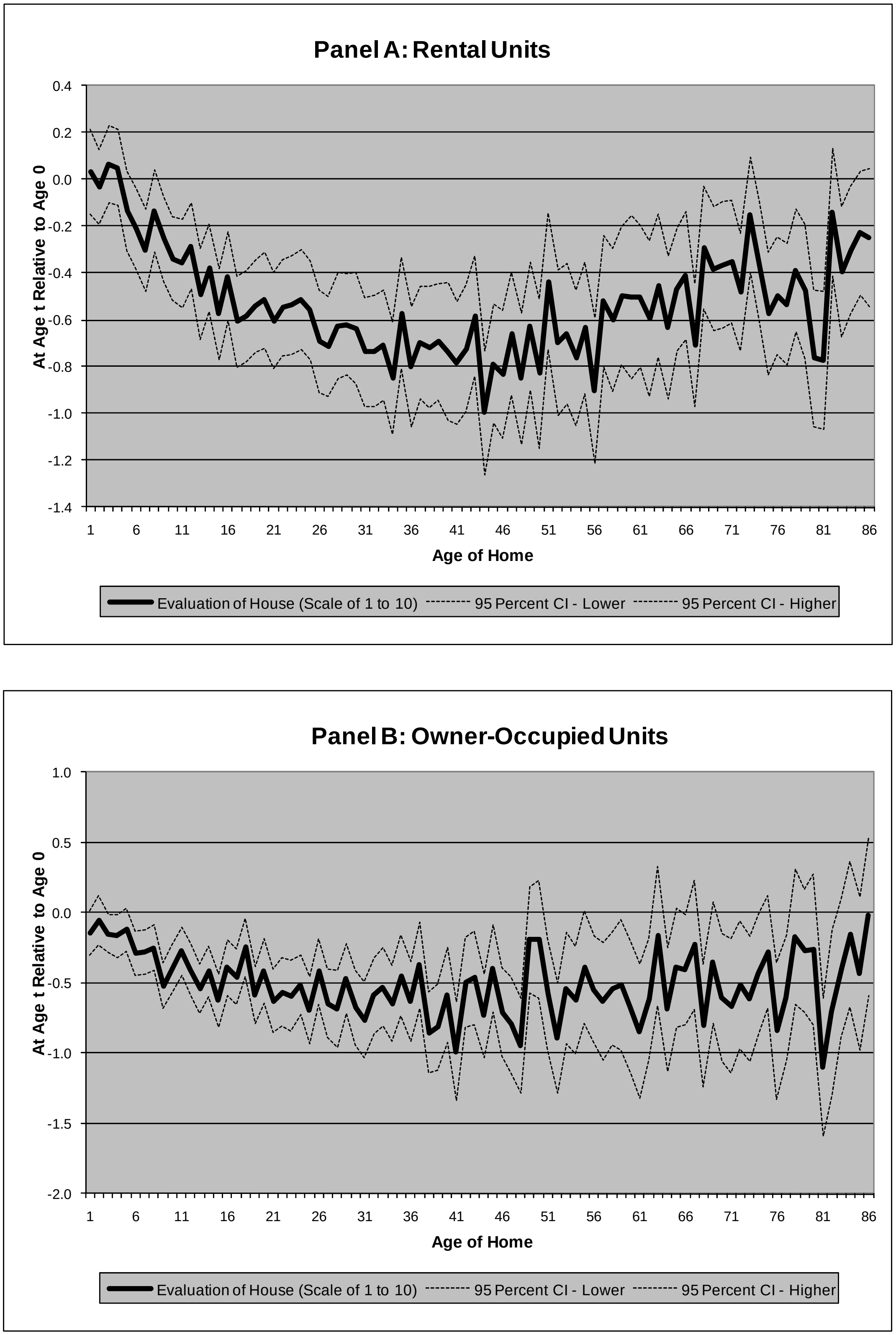


Figure 5a: FHFA Home Purchase Price Indexes
Adjusted for Inflation Using the CPI-U

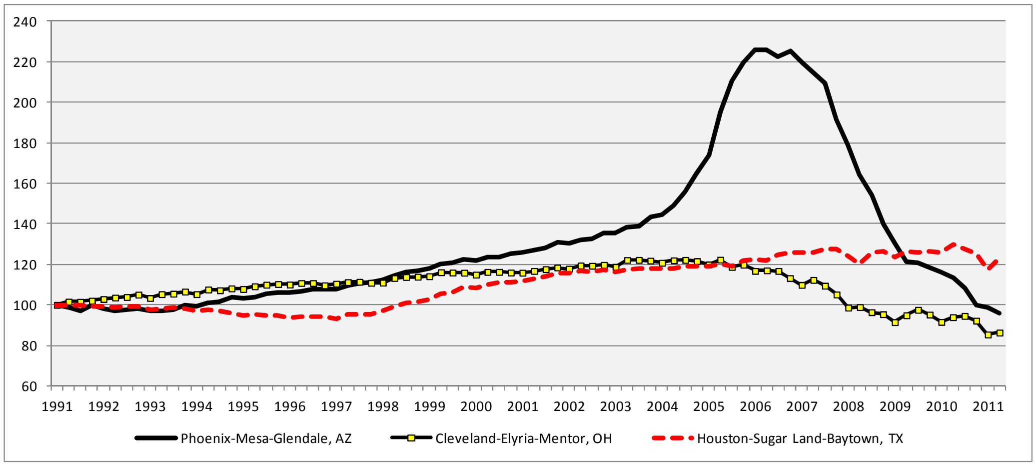


Figure 5b: Simulated Filtering of Rental Housing Unit Based on
Real Income (Panel A) Col (6) Table 2 Estimates and 0.2 x ΔFHFA Index

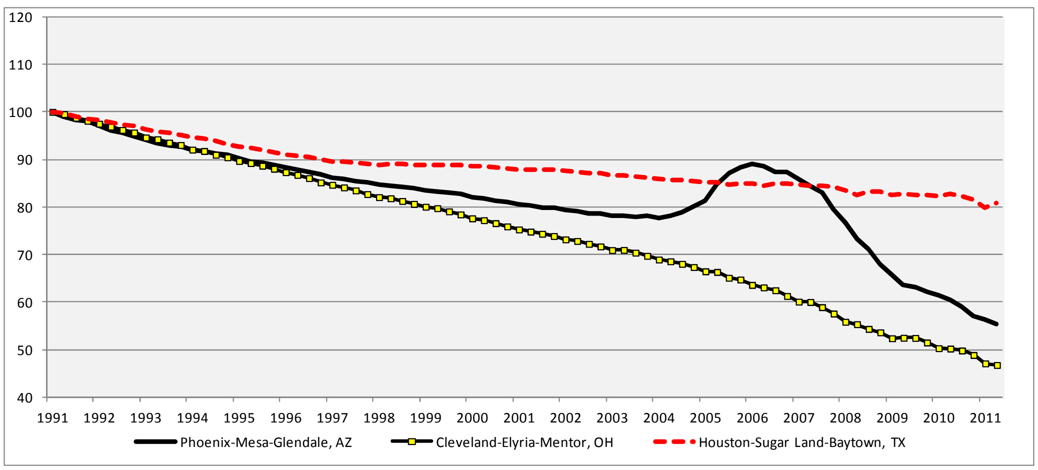
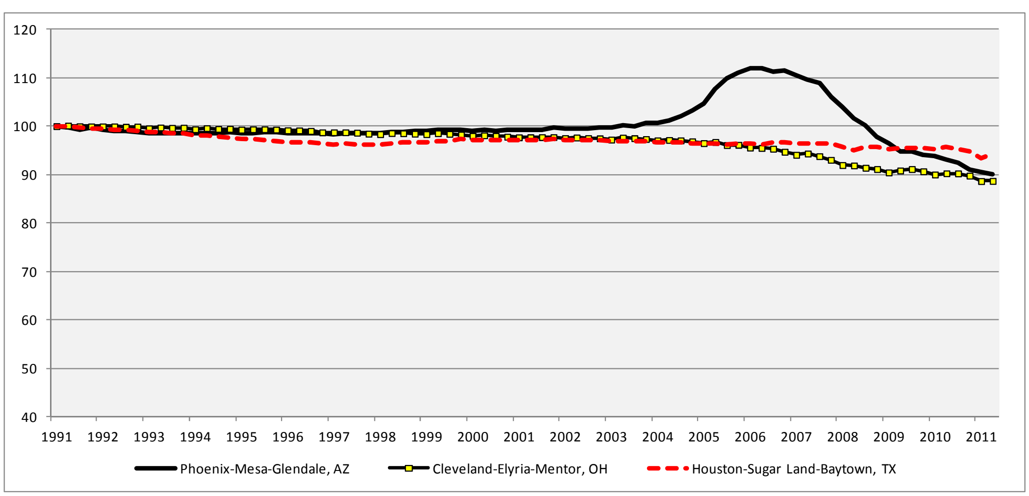


Figure 5c: Simulated Filtering of Owner-Occupied Housing Unit Based on
Real Income (Panel A) Col (5) Table 3 Estimates and ΔFHFA Index



Appendix: First-Stage Regressions

Table A-1: First Stage Regressions for GMM Models
(t statistics in parenthesis are based on robust standard errors)

	Rental Units			Owner-Occupied Units		
	Table 2 Model 3	Table 2 Model 4	Table 2 Model 5	Table 3 Model 3	Table 3 Model 4	Table 3 Model 5
Years Between Turnovers	.00696	0.00223	.00214	.01025	-0.0086	-.01011
	(8.12)	(2.13)	(2.02)	(5.00)	(-3.80)	(-4.26)
2nd Turnover in the 1980s	.01418	-	.02575	-.06096	-	.10117
	(1.58)	-	(2.83)	(-1.73)	-	(2.72)
2nd Turnover 1990 to 1996	.00832	-	.02746	-.14398	-	.06081
	(1.11)	-	(3.53)	(-5.70)	-	(2.03)
2nd Turnover 1997 to 2005	.03699	-	.04259	.01798	-	.14323
	(5.06)	-	(5.80)	(0.76)	-	(5.58)
ΔFHFA Price Index Between Turnovers	-	0.00059	.00061	-	0.00293	.00308
	-	(8.74)	(8.59)	-	(14.86)	(13.20)
MSA Fixed Effects	147	147	147	144	144	144
Observations	49,128	49,128	49,128	11,754	11,754	11,754
Within R-Sq	0.0031	0.0039	0.0046	0.0137	0.0294	0.0334
Root MSE	.4951	0.4949	.4947	.8086	0.8021	.8005