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Using Home Maintenance and Repairs to Smooth Variable Earnings[1]

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Abstract

Recent research documents a significant increase in U.S. transitory income variance over the past twenty-five years. An emerging literature explores the role of durables in the household's attempt to smooth consumption over these movements in transitory income. This paper examines the degree to which homeowners adjust their home maintenance decisions in order to offset transitory income fluctuations. *American Housing Survey* data shows that home maintenance expenditures are economically significant, amounting to nearly $2,100 per year. We find a statistically significant positive elasticity of maintenance expenditures to estimated transitory income changes. However, the results suggest that adjusting home maintenance expenditures plays a relatively minor role in the household's overall consumption smoothing strategy. In terms of actual dollars, deferred home maintenance offsets on average from 1 to 7 cents of each dollar of transitory income loss.

1 Introduction

Transitory fluctuations in family income have increased substantially over time, and clearly would impose hardships if consumption had to move in sync with income. Moffitt and Gottschalk (1994, 1995) use *Panel Study of Income Dynamics* (*PSID*) data to document that transitory income variance increased 42 percent between 1970-78 and 1979-87, from just over 12 percent to just over 22 percent of annual income. More recently, Cameron and Tracy (1998) use *Current Population Survey* (*CPS*) data to show that transitory income variance increased by two-thirds between 1967-71 and 1992-96, with the largest increases being for the least educated households.

In this paper, we investigate the extent to which owner-occupied households use their homes to smooth consumption. The potential relevance of housing in this respect is illustrated in Figure 1's plot of the life-cycle pattern of financial and durable assets. Figure 1 shows median household asset allocations by age of the household head based on the 2001 *Survey of Consumer Finances* (*SCF*). Young households accumulate financial assets in part for a downpayment on a house. As households make the transition to homeownership, their share of non-retirement financial assets falls below 20 percent. This financial asset share remains quite stable until households reach their mid-50s, after which households steadily increase their financial asset share in preparation for retirement. Note that the household median durable asset share declines with the age of the household but exceeds fifty percent throughout the life-cycle. Figure 2 plots durable assets disaggregated into housing and other durables. The dominate role of housing in the household portfolio is clearly evident here. The median housing asset share rises until age 45, levels off at around 40 percent between the ages of 45 and 65, and then trends higher as households enter retirement.

Interest in the role of durable goods in a household's consumption smoothing strategy dates at least to Attanasio's (1977) finding that the variance of log income is greater than the variance in nondurable expenditures, but lower than that for durable expenditures. More recently, Dynarski and Gruber (1997) use the *Consumer Expenditure Survey* (*CEX*) and estimate an income elasticity of 0.89 for durables consumption that is much greater than their income elasticity estimate for nondurables consumption of 0.11.

Two views on the role played by durable goods in the household's management of consumption have emerged. Fernandez-Villaverde and Krueger (2002) argue that younger households typically smooth nondurable consumption using durable assets instead of financial assets. Older households, they maintain, accumulate financial assets primarily to help finance consumption during retirement. In this view, durables serve as collateral for borrowing during times of income shortfalls. In contrast, Browning and Crossley (1999) consider classes of goods (such as clothing) which have little or no collateral value, and view the postponement of the replacement decision as a method for generating cash flow that the household can use to finance nondurables consumption. Browning and Crossley find evidence supporting this 'internal capital markets' perspective on the role of durables by looking at the consumption decisions of a sample of unemployed Canadian workers.

Because houses can provide collateral for loans as well as require significant ongoing maintenance expenses, they can be used to smooth nondurable consumption in either of the two ways described in the literature. Our analysis in very much in the spirit of Browning and Crossley's (1999) 'internal capital markets' perspective.[2] That is, we focus on the degree to which homeowners adjust the timing and magnitude of home maintenance expenditures in response to transitory income movements.

The *American Housing Survey* (*AHS*) documents that average annual maintenance and repair expenditures for homeowners are substantial at \$2,051 (equal to 3.5 percent of household income). There is little empirical evidence, though, on whether deferral of home maintenance and repair spending is used to generate current cash flow to make up for transitory income shortfalls. While not the focus of their study, Dynarski and Gruber (1997) report an income elasticity for "home services" of 0.60 (see their Table 4). Home services in the *CEX* capture primarily home repair and maintenance activities. This elasticity is second in magnitude only to their reported income elasticity for durable goods.

We build on Dynarski and Gruber's approach using an alternative data source, the *AHS*. The *AHS* data is particularly well suited to an analysis of the role of housing in

[2]See Hurst and Stafford (2004) for an analysis of the 'durables as collateral' view of housing.

consumption smoothing, as it allows us to look at income changes over wider time intervals than the *CEX* (two years versus nine months) and to control for characteristics of the household, the neighborhood, and the local housing market which could influence the estimated elasticities. In addition, we can disaggregate the results by demographic characteristics of the household head and by specific type of maintenance activity in order to gain additional insight into the household's home maintenance decisions.

We find that homeowners do adjust their maintenance activities in order to offset fluctuations in transitory income. The elasticity of maintenance and repair spending with respect to our estimate of transitory income changes is 0.41 in our preferred IV specification. That two very different data sources (*CEX* and *AHS*), each with its own strengths and weaknesses, find a statistically significant impact should increase our confidence in the result. In terms of actual dollars, deferred home maintenance offsets on average from 1 to 7 cents of each dollar change in estimated transitory income. Thus, our results indicate that the economic importance of home maintenance for consumption smoothing is somewhat limited, with the impact not much different from Dynarski and Gruber's (1997) estimate that households adjust clothing expenditures by 1.1 cents in response to a dollar change in income.

The role played by durables in buffering income changes might be expected to be more important for households that are liquidity constrained. In an analysis of owners' use of their homes as collateral for refinancing, Hurst and Stafford (2004) report that liquidity constrained households convert well over half the equity removed via refinancing into current consumption, while they find no such evidence for unconstrained households who refinance. We can not identify liquidity constrained households in the *AHS* data using the Hurst and Stafford methodology. As an alternative, we look at first-time homebuyers within five years of the purchase date who have not completed a cash-out refinance of their mortgage. To the extent that these households converted most of their liquid assets into the down payment on their home, we would expect these households to be relatively liquidity constrained. Among households aged 20 to 39, we estimate that the permanent income elasticity is 0.62 for unconstrained households and 1.11 for constrained households. Transitory income elasticities are similar in magnitude across these two groups of households.

It is also noteworthy that a single type of maintenance or repair decision does not drive our estimated elasticity of maintenance expenditures to transitory income changes. Whether for routine maintenance, for a new or remodeled kitchen or bath, or for insulation, storm doors or windows, owners appear to be willing to defer maintenance to free up income for nondurable consumption. That said, there is no evidence of an 'internal capital markets' role for two specific maintenance and repair categories examined: a new roof and new siding. These two cases are more likely to exhibit something closer to one-hoss shay depreciation, so that deferral of necessary maintenance would not be part of a sensible consumption smoothing strategy.

Finally, the fact that home maintenance is used by all types of households to smooth consumption probably is due to the fact that this method has much lower fixed costs than refinancing and can be used even if mortgage rates are rising. While our findings indicate that owners do not use their homes to buffer a major portion of the income variability they face, the broad class of expenditures that fit into the "internal capital market" view of consumption smoothing may combine to offset as much as 20 percent of income changes.[3]

2 Data and Econometric Issues

To estimate the elasticity of home maintenance expenditures to transitory income fluctuations, we must observe both changes in household income and changes in household expenditures on home repair, maintenance, and improvements. In addition, enough demographic and household composition variables must be available to permit measurement of transitory income variations about a life-cycle income path, as well as to control for any changes in a household's preferences for housing services.

Since 1985, the *AHS* has been conducted every two years on a continuous panel of houses. The *AHS* data contain a unique identifier for each house, an indicator for whether the house is owned or rented, and the year in which it was purchased if the unit is owned. We restrict our attention to owned homes. For this subsample, the house

[3]See Dynarksi and Gruber's Table 4 (1997). The combined effect for durables, clothing and home services is 21 cents per dollar change in income.

identifier and the purchase year allow us to track the same households across surveys.[4] The *AHS* data also provide detailed household demographic information that allows us to estimate a simple model of transitory income fluctuations, as well as control for likely changes in household preferences for housing services. In addition, the *AHS* panel covers much of the 1980-1993 period examined by Dynarski and Gruber (1997), thereby allowing us to compare results over a similar time period using different data.

There are two approaches to isolating transitory income fluctuations. The first approach is to find instruments for transitory income changes. Examples might include an indicator for temporary layoffs and changes in hours worked. This approach is difficult to implement with the post-1985 *AHS* data since it does not include most of the candidate instruments that have been used in the literature.[5] The second approach is to assume a specific model for the earnings process and then use the structure of that model to construct the transitory income component. We follow this strategy.

Consider the following specification for household earnings,

$$(1)\quad \ln(Y_{it}) = X_{it}\beta + \mu_{it} + \varepsilon_{it} \quad ,$$

where Y_{it} is the i^{th} household's earnings in year t, X_{it} is a set of demographic and human capital variables capturing life-cycle earnings profiles, μ_{it} is the permanent component of residual earnings, and ε_{it} is the transitory component of residual earnings. The permanent component is typically modeled either as a random walk or a heterogeneous growth process.[6] Baker (1997) tests the random walk specification against the

[4]There are, however, numerous missing or inconsistent values for the purchase year. We systematically edited these observations using information on the purchase year in adjacent data points involving the same house and characteristics of the household head and family size. Doing so substantially increases the size of the sample used in the estimation (by about 30%) and increases the average length of the panel for each household. Those details are available upon request.

[5]Morever, Altonji and Siow (1987) show that this approach can be problematic even when the data includes such instruments. For example, using the *Panel Study of Income Dynamics*, they report that temporary layoffs are not a significant predictor for household income changes. Thus, at least some of the candidate instruments are not very powerful.

[6]On the random walk specification, see MaCurdy (1982), Abowd and Card (1989), Topel (1991), Topel and Ward (1992), and Moffitt and Gottschalk (1995). For the heterogeneous growth specification, see Lillard and Weiss (1979), Hause (1977), MaCurdy (1982), Moffitt and Gottschalk (1995), and Haider

heterogeneous growth specification as given in equation (2) using *Panel Study of Income Dynamics* data and a common set of controls for the life-cycle earnings profiles,

(2) $\mu_{it} = \gamma_i + \lambda_i Exp_{it}$,

where Exp_{it} is the potential labor market experience for the i^{th} household. He finds the data to be more supportive of the heterogeneous growth specification.

We use the heterogeneous growth specification to estimate the transitory residual earnings component in two steps. In the first step, equation (1) is estimated by regressing log earnings on a set of demographic and human capital variables.[7] In the second step, equation (2) is estimated for each household by regressing its earning residuals $(\mu_{it} + \varepsilon_{it})$ on the household head's potential labor market experience, which is measured as the age of the head minus imputed years of schooling minus six. The residuals from these second-stage regressions serve as our estimates of the transitory residual earnings component, ε_{it}.[8] Using these estimates, we can decompose family log earnings into its permanent component ($\ln Y_{it}^P \equiv X_{it}\hat{\beta} + \hat{\gamma}_i + \hat{\lambda}_i Exp_{it}$) and its transitory component ($\ln Y_{it}^T \equiv \varepsilon_{it} + \hat{m}_{it}$), where $\hat{m}_{it}$ represents the combined effects of measurement and estimation error.

Following Dynarski and Gruber (1997), we restrict our sample to households with heads between the ages of twenty and fifty-nine. In contrast to those authors, we include female-headed households as well as male-headed households. We drop observations if any of the income variables are allocated, and further restrict the sample to houses located in 114 SMSAs for which we can merge in Freddie Mac repeat-sale

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(2001).

[7]The control variables include the following demographic variables for the household head: a cubic in age, indicators for gender and race (white-nonwhite), marital status, and four educational attainment categories. We also include an indicator for whether the spouse works.

[8]As discussed below, consistent maintenance data exists in the *AHS* only from 1985 to 1993. However, we use earnings data from 1985 to 2003 to estimate the heterogeneous growth model for each household. We require that a household participate in at least three surveys to be included in our estimation.

house price data. Metro area house price data is employed to control for possible home "equity" effects on the household's maintenance decision.

For the years 1985-1993, the *AHS* asked a consistent series of questions on home maintenance/ repair/improvement activities (hereafter referred to as maintenance activities) undertaken by the household over the prior two years. More specifically, the survey reports how much households spent over the past two years on each of ten maintenance activities. Table 1 lists these maintenance categories along with summary statistics for the real expenditures in each category for our sample of households.[9,10] Summing across the categories, 90 percent of homeowners make positive maintenance expenditures over a two-year period. Conditional on positive maintenance expenditures, the average yearly maintenance expenditure is \$2,279. The average yearly unconditional maintenance expenditure is \$2,051. The average ratio of the annualized unconditional maintenance expenditures to the reported house value is 1.7 percent, while the ratio to household income is 3.5 percent. In the analysis below, we follow Dynarski and Gruber (1997) in treating these expenditures as expenses rather amortizing them over time.

To estimate the extent that homeowners offset transitory income variation through changes in home maintenance activities, we begin with a simple regression framework described in equation (3).

$$(3) \quad \ln(M_{irt}) = \alpha_i + \beta_Y \ln Y_{it} + X_{it}\delta + Z_{rt}\gamma + \eta_{it} \quad ,$$

where M_{irt} is the i^{th} household's 2-year maintenance expenditure, X_{it} is a vector of

[9]We combine the new insulation and storm doors/windows categories. Routine maintenance expenditures are reported for the prior year. We double those expenditures to make them comparable to the other expenditure categories.

[10]In each year, these nominal expenditures are right-censored at \$9,997. Many households have missing expenditure values for one or more maintenance categories. For households that indicate they did not engage in a particular maintenance activity, we treat a missing expenditure for that activity as a zero. However, we exclude from the estimation any household that indicated it did engage in a particular maintenance activity, but reports a missing dollar expenditure.

education/demographic characteristics for the household head, household composition variables and an indicator for the first year in a house[11], and Z_{rt} is a vector of house, neighborhood and SMSA characteristics. Examples of this type of empirical specification can be found in Mendelsohn (1977) and Reschovsky (1992).

Using our decomposition for family earnings discussed earlier, we can rewrite equation (3) allowing for differential income elasticities for the permanent and transitory income components as follows

$$(4) \quad \ln(M_{irt}) = \alpha_i + \beta_P \ln Y_{it}^P + \beta_T \ln Y_{it}^T + X_{it}\delta + Z_{rt}\gamma + \eta_{it} \, .$$

The coefficient of particular interest for the smoothing hypothesis is the income elasticity of maintenance to transitory income changes, β_T.

Preferences for home maintenance may systematically differ across households in ways that are not well captured by our demographic controls. To the extent that these unobserved household-specific preferences are relatively constant over time, α_i , we can eliminate their influence by estimating equation (4) in first-differences within households,

$$(5) \quad \Delta \ln(M_{irt}) = \beta_P \Delta \ln Y_{it}^P + \beta_T \Delta \ln Y_{it}^T + \Delta X_{it}\delta + \Delta Z_{rt}\gamma + \Delta \eta_{it} \quad .$$

In equation (5), the 2-year change in log maintenance expenditures is regressed on the 2-year changes in household permanent and transitory income, any changes in the household's characteristics (i.e., changes in marital status or family size), the age of the household head[12], a lag indicator for the first year in a house, and changes in neighborhood and SMSA characteristics. Since many of the controls used in equation (4) are constant over 2-year intervals, equation (5) involves fewer control variables.[13]

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[11] This last variable is included to capture any unusual maintenance activity that occurs during a household's first year of residence.

[12] The age of the household head is included to pick up any curvature in the average life-cycle maintenance profile.

[13] In particular, house-specific characteristics that may impact maintenance such as year built and type of

We extend Dynarski and Gruber's (1997) basic specification to include controls for changing conditions in the neighborhood and the local housing market. At the neighborhood level, we include an indicator for whether the household felt that their neighborhood had significantly improved or worsened over the past two years. Household maintenance decisions may also depend on the degree of recent price appreciation in their local housing market. We control for this by including the 2-year house price appreciation rate for the metropolitan area based on the Freddie Mac repeat-sale price index. Finally, we include region and year fixed effects in order to capture any persistent differences in aggregate maintenance trends across large geographic areas and over time.

Beyond the modeling issues discussed above, there are important measurement and specification error issues involved in obtaining an unbiased estimate of β_T needed to confirm or reject the hypothesis that home maintenance plays a role in smoothing consumption. They work in opposite directions, and we discuss below whether one effect is likely to dominate the other.

Measurement error in reported earnings changes is known to be large. In their comparison of matched *CPS* data with social security earnings records, Bound and Krueger (1991) estimate that 20-25 percent of the variation in reported income changes is due to measurement error. While we are unaware of any similar study of measurement error in the *AHS*, this survey likely suffers from similar problems to those found for the *CPS*. Left uncorrected, measurement error in the income changes will lead to measurement error in our estimates of transitory income changes, resulting in downward-biased estimates of β_Y and β_T.

Countering this is the possibility that at least some of the mismeasurement of transitory income changes arises from conflating them with permanent income changes. In this case, a wealth effect generated from an unanticipated permanent income change could be misconstrued as consumption smoothing. As noted above, our estimate of transitory income can be thought of as the underlying true transitory income plus an error component that captures both measurement and specification error, or $\ln Y_{it}^T \equiv \varepsilon_{it} + \hat{m}_{it}$. To the extent that the error component largely reflects specification

construction drop out of equation (5).

error whereby we misclassify permanent income changes as temporary income changes, this leads to upwardly biased estimates of β_T.[14]

Focusing initially on measurement error, we discuss the steps we take to minimize it. After reporting our key results, we return to the specification error issue and discuss its likely importance. To preview that discussion, we are not able to find any evidence consistent with our measure of transitory income changes being seriously contaminated by specification problems confounding permanent and transitory income changes. That said, we cannot completely rule out the possibility of specification bias.

Altonji and Siow (1987) advocate addressing measurement error in reported income by using a set of income determinants to instrument for reported income.[15] Dynarski and Gruber (1997) pursue this strategy and construct an alternative measure of income using information on the hourly wage, usual weekly hours, and weeks worked. The post-1985 *AHS* data does not ask questions on wage rates or hours/weeks worked, nor does it contain indicators for events associated with significant transitory income changes.

While we can not duplicate the Altonji and Siow IV strategies because of data limitations, the logic behind using income determinants as instruments still is sound if they are subject to their own sources of measurement error that are not strongly correlated with the measurement error in reported income. Hence, we searched the *AHS* for other potential instruments. The survey does contain a question asking the household to report the amount of "other income" that it received.[16] This variable is meant to capture the non-wage and salary components of household income including business, dividend, rental, welfare, SSI, alimony, child support, and unemployment or

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[14] This is the case if the permanent income elasticity of maintenance expenditures exceeds that for transitory changes, which is what we find in the data. Our IV strategy for estimating β_T while designed to correct for measurement error also provides protection against this form of specification bias.

[15] These determinants can include constructed income measures from information on wages, weeks and hours worked, as well as indicators for events that are associated with income changes such as unemployment spells, illness, quits and promotions.

[16] Specifically this is the variable VOTHER in the *AHS* data. Prior to 1985 the *AHS* survey contained an indicator for whether an individual had received any unemployment compensation. However, this question was dropped from the *AHS* survey starting in 1985.

workmen's compensation. We use the 2-year percent change in this other income as an instrument for the 2-year change in log transitory household income.

Another set of instruments we use is motivated from the idea that local labor markets have their own idiosyncratic cycles [see Topel (1986)]. In any year, wages in a particular local labor market will reflect the impact of local labor demand and supply shocks. To incorporate this idea, we extend the definition of the transitory income component presented above to

$$\ln Y^T_{ijt} = \alpha_{jt} + \varepsilon_{it} + m_{it} \quad ,$$

where α_{jt} represents the impact of transitory shocks to the j th local labor market and ε_{it} now captures the purely idiosyncratic component to the i th household's transitory income.

Two strategies are employed using this structure for the household's transitory income to generate additional instruments. First, we assume that the measurement error component, m_{it}, is uncorrelated across households for a given year. For each SMSA and year, we average the transitory income changes for all of the households in that SMSA (except for the i th household). This group average should be correlated with the transitory income change for the i th household through the local labor market effects, α_{jt}.

The second strategy uses an alternative source of data to estimate the α_{jt} terms, specifically the Bureau of Economic Analysis (BEA) Regional Economic Information System (*REIS*) data. Real earnings per worker are computed for the SMSAs in our sample for the period 1969-2001.[17] We drop the even years from the sample (to match the *AHS* where the samples overlap) and construct the 2-year differences in log real earnings per worker. We regress these 2-year log real earnings changes on a set of SMSA fixed effects, a set of year effects, and the lag 2-year log real earnings change. We use the residuals from this regression as an additional instrument for the α_{jt}.

Our third set of instruments is generated using a variant of the "grouping" method suggested by Wald (1940), Bartlett (1949), and Durbin (1954). For each year in our sample, we estimate where a household is in the distribution of 2-year income changes for that year and census region. Indicators are constructed for the different quantiles of these distributions for each year and census region. We then use these indicators for quantile changes as instruments for the observed income changes. This choice of instruments will filter out measurement error in the income changes that do not move the household between different quantiles of the relevant regional distribution.

The final part of our strategy involves constructing the sample in an effort to minimize problems that might arise due to measurement error. As noted earlier, we drop all observations that include imputed values for household income. Including these observations would introduce imputation errors in our measure of transitory income shocks. In addition, we symmetrically trim the top and bottom one percent of the measured income changes, thereby eliminating the most extreme outliers.

A second econometric issue becomes important when we look at changes in expenditures for specific maintenance categories. As is evident from Table 1, for most of these maintenance categories there is a significant fraction of households that make no expenditures of that type over the two-year period. For many of the maintenance categories, a sizeable fraction of households also make no expenditures over successive two-year periods. This implies that a significant fraction of the 2-year maintenance changes will be zero.

This feature of the data suggests using a "friction" estimator [see Rosett (1959)] when we estimate equation (5) for specific maintenance categories. The basic idea behind this estimator is illustrated in Figure 3. Let ΔM^* denote an unobserved index of a household's desired change in a particular maintenance expense, and let ΔM denote the household's observed change in expenditures for that maintenance category. We model ΔM^* as a continuous latent variable. Friction models capture the propensity for zero changes in the data by assuming that small changes in desired expenditures (positive or negative) do not generate any actual changes in maintenance expenditures.

[17] Information on the BEA REIS data can be found at: http://infoserver.ciesin.org/datasets/reis/reis-home.html. Details of the sample construction are provided in the data appendix.

The degree of censoring is captured by the parameters α_1 and α_2 in the specification below.

The friction model is given by the following set of equations.

$$\Delta \ln(M^*_{irt}) = \beta\Delta\varepsilon_{it} + \Delta X_{it}\delta + \Delta Z_{rt}\gamma + \Delta\eta_{it}$$

(6)
$$\Delta \ln(M) = \begin{cases} \Delta \ln(M^*_{irt}) - \alpha_1 & \text{if } \Delta \ln(M^*_{irt}) < \alpha_1 \\ 0 & \text{if } \alpha_1 < \Delta \ln(M^*_{irt}) < \alpha_2 \\ \Delta \ln(M^*_{irt}) - \alpha_2 & \text{if } \Delta \ln(M^*_{irt}) > \alpha_2 \end{cases}$$

We calculate the maintenance elasticities from the friction model as the "unconditional" marginal effect ($\mathrm{ME_u}$), which is defined as the average derivative across our estimation sample.

(7)
$$\mathrm{ME}_U = \partial \ln(M_{it}) \Big/ \partial \ln(Y^T_{it}) = \frac{1}{N}\sum_{i=1}^{N}\left[1 - \left(\Phi(Z_{it} \mid \alpha_2) - \Phi(Z_{it} \mid \alpha_1)\right)\right]\beta_T \quad ,$$

where $Z|\alpha$ represents the standardized control variables, and Φ is the standard normal cumulative density. This method of constructing the marginal effect takes into account the nonlinearities in the friction model.

3 Empirical findings and discussion

Summary statistics on all of our control variables are given in Appendix Table A1, and the results for the estimation of equation (5) are reported in Table 2.[18] The first row of that table indicates that the overall income elasticities of maintenance expenditures are 0.42 (OLS) and 0.47 (IV). Thus, households do adjust the intensity of home maintenance activity to take account of income changes. If this adjustment process takes longer than two years, then our elasticity estimates would underestimate the full impact of overall income changes on maintenance expenditures. We checked for this

[18] The instruments are jointly significant in the 1st-stage regressions for both the overall income changes and the transitory income changes. Those results are available upon request.

possibility by including the lagged income change in equation (5). The coefficient on this variable was small in magnitude and statistically insignificant.

The next issue examined is whether the magnitude of the maintenance adjustments depend on the nature of the income change. When we allow the income elasticities to differ in response to our estimate of permanent as compared to transitory income changes, the results suggest that the elasticity with respect to permanent income movements is larger (0.62 versus 0.38 via OLS and 0.63 versus 0.41 via IV; see the second and third rows of Table 2). However, these results are not precise enough for us to reject at standard confidence levels the hypothesis that permanent and transitory income elasticities are equal.[19]

While the transitory income elasticities are statistically significant, they also imply that owners are using home maintenance effort to buffer only a relatively small fraction of the changes to transitory income. If we scale the transitory elasticity by overall average income, then the IV estimate implies that on average households adjust their maintenance expenditures by 1.2 cents for every dollar change in transitory income. This is lower than the IV estimate of 2.2 cents per dollar reported in Dynarski and Gruber.[20] However, a dollar change in transitory income surely represents a larger percentage change than a dollar change in overall income. The difficulty is coming up with an appropriate scaling given that, by construction, the sample average transitory income should be close to zero. As an alternative scaling factor, we compute the average absolute value of the transitory income component. Using this as our scaling factor, a dollar change in transitory income is associated with a maintenance offset of 6.5 cents. Thus, depending on the choice of scaling, the results indicate that households use maintenance expenditures on average to offset from 1 to 7 cents of every dollar change in transitory income.

We also tested for the presence of asymmetric income effects to see if our estimated income elasticities are being driven primarily by positive or negative income

[19] The F-tests [and probability values] for the null of equal elasticities are 2.52 [0.11] (OLS) and 2.23 [0.14] (IV).

[20] The Dynarski and Gruber estimate is not strictly comparable to our transitory elasticity in that in the *CEX* data they can not estimate the random growth specification given in equation (2). Their

changes. For all of the income elasticities – overall, permanent, and transitory – we find for the full sample no evidence of any asymmetry in the response to favorable as compared to unfavorable income movements. Households appear to both increase maintenance expenditures when faced with favorable income developments, and decrease maintenance expenditures when faced with adverse income developments.

Given the paucity of research on the determinants of home maintenance expenditures, we briefly summarize the other findings in Table 2 before turning to analyses of the effects across household types and categories of maintenance activity. We find evidence that households engage in a significant amount of maintenance activity in the first year of residence in a home.[21] We do not find evidence of any meaningful curvature in the average household life-cycle maintenance profile. Increases in household size lead to higher maintenance activity by households, but this effect is imprecisely estimated. Transitions into and out of marriage are associated with reductions in home maintenance (beyond the level implied by a change in family size), but the magnitudes of these effects are also imprecisely estimated. We find no evidence of an "equity" effect on maintenance decisions operating though the rate of appreciation in SMSA house prices. However, controlling for average price appreciation in the SMSA, we do find that homeowners spend on average 20 percent less on maintenance when they report that their neighborhood has improved significantly. Conversely, maintenance expenses also tend to increase when homeowners report that their neighborhood has declined significantly, though this effect is smaller in magnitude and is imprecisely estimated.

One benefit of the *AHS* is that we can investigate whether maintenance elasticities vary across different types of households. For example, the role played by durables in buffering income changes might be expected to be more important for households that are liquidity constrained. Consistent with this view, Hurst and Stafford (2004) report that households without liquid assets who experience a spell of unemployment are 25 percent more likely to refinance than other households, and conditional on a refinance

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specification does partially control for permanent income changes due to observed factors such as age and education.

are 12 percent more likely to remove equity in the process. Furthermore, among unconstrained households the more predictable the changes in permanent income the less we would expect maintenance expenditures to vary with these changes.[22]

Because we can not observe either recent unemployment spells or a household's liquid assets in the AHS[23], we appeal to our earlier discussion of Figure 1 to gain insight into these issues. As suggested by that figure, young households accumulate financial assets in order to fund a downpayment on a house. For first-time homebuyers, the purchase of a house is likely to coincide with a significant reduction in their portfolio of financial assets. We identify liquidity constrained households, then, as first-time homebuyers within five years of the purchase date who have not completed a cash-out refinance of their mortgage. For our overall sample, 14 percent of households meet this definition, and we would expect the permanent income elasticity to be larger for this group.

To explore the question of how the degree of predictability of permanent income changes impacts the permanent income elasticity, we split the sample by age and look at household heads aged 20-39 and household heads at least 40 years of age. Experience in the labor market should help households both to understand the average life-cycle earnings pattern captured in equation (1) as well as their own individual earnings heterogeneity about this average profile as captured in equation (2), thus increasing the predictability of their permanent income changes. We would expect, then, the impact of permanent income changes on maintenance activity to fall with age.

Table 3 reports IV estimates of our maintenance elasticities disaggregated by age and within the young sample by our liquidity constraint indicator.[24] Initially considering young households shows the permanent elasticity increasing from 0.62 to

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[21] When we difference the data, the first-year residence indicator variable takes the value of 0 or −1. If households do relatively more maintenance in their first-year of residence, then this should show up as a negative coefficient in the difference regression.

[22] We thank a referee for raising this point.

[23] The *AHS* does ask if the household has at least $20,000 in savings/investments. However, less than one percent of our estimation sample answered this question in the affirmative.

[24] The incidence of our measure of liquidity constraints for the older sample of households is too small to consider estimating both constrained and unconstrained elasticities.

1.11 as we move between the unconstrained and the liquidity constrained households.[25] This is consistent with the view that liquidity constraints are one factor that contributes to positive permanent income elasticities. This table also reports evidence consistent with the hypothesis that absent liquidity constraints as permanent income changes become more predictable maintenance effects are attenuated. For young households that are not liquidity constrained by our measure, the permanent income elasticity is 0.62. In comparison, for older unconstrained households the permanent income elasticity is 0.5. In contrast, household age appears to have less of an impact on the transitory elasticity.

In Table 4, we examine the impact of transitory income changes on individual maintenance expenditure categories. With the exception of roof, siding and other expenditures, each individual maintenance category exhibits an income elasticity of at least 0.10. The essentially zero elasticities for roof and siding expenditures indicate that households do not buffer transitory income swings via spending on these activities. A likely explanation is that these particular maintenance categories are less discretionary in nature. That is, if a household's roof is leaking, the household has a strong incentive to spend something on repairs regardless of the transitory income realization the household may be experiencing at that time. Thus, there is no indication that a single type of maintenance category is driving the aggregate results reported above. However, there does appear to be a small subset of home maintenance categories that do not fit well into Browning and Crossley's internal capital markets' role for durable goods.

4 A Robustness Check

Because a potential concern regarding the robustness of our findings arises from mismeasurement of transitory income and especially its conflation with permanent income, we conducted additional analysis to be more confident that the impacts reported above can, in fact, reasonably be interpreted as responses to transitory income changes. As was discussed earlier, our estimate of transitory income can be thought of

[25] The difference in elasticities, though, is not statistically significant.

as the underlying true transitory income plus an error component which captures both measurement and specification error, $\ln Y_{it}^{T} \equiv \varepsilon_{it} + \hat{m}_{it}$. To the extent that this error component largely reflects measurement error, if left uncorrected it will lead to downward biased estimates of the transitory income elasticity of maintenance expenditures (β_T). However, if the error component largely represents specification error where we misclassify permanent income changes as transitory income changes, then this will lead to upward biased estimates of β_T.

Since our specification is estimated in first differences, the impact of measurement and specification error on β_T will depend on the degree of persistence in these two types of errors. The more persistent the underlying error process, the more its impact will be attenuated in the differenced data. Griliches and Hausman (1986) show that if true earnings and measurement error are stationary series, then the reliability of the first-difference in reported earnings is given by the following.

$$(8) \quad \lambda = \frac{\sigma_y^2}{\sigma_y^2 + \sigma_m^2[(1-\rho)/(1-r)]} \quad ,$$

where σ_y^2 is the variance of true earnings, σ_m^2 is the variance of the measurement error, ρ is the first-order serial correlation in the measurement error and r is the first-order serial correlation in true earnings. If, for example, the positive serial correlation in true earnings exceeds the positive serial correlation in the measurement error, then first-differencing the data will reduce its reliability. Hence, knowledge of the serial correlation in the measurement and specification error would be helpful.

There is evidence from Bound and Krueger (1991) on the degree of serial correlation in the measurement error of self-reported earnings, and it is not very high. Using matched *CPS* data from 1977 and 1978 linked to Social Security payroll tax records, they report that the ratio of the variance of the signal to the total variance in the cross-section is 0.82 for men and 0.92 for women. Those ratios fall to 0.65 for men and 0.81 for women when the data are first-differenced. In contrast, our sense is that any misattribution of permanent income shocks as transitory shocks is likely to be strongly correlated over time. For example, most types of disabilities that we cannot directly observe are likely to affect wages over long time periods. Thus, estimating equation (5) with differenced data will tend to exacerbate any measurement error, while we suspect it will tend to mitigate any specification error.[26]

We also addressed this issue directly in our data. One way to investigate the possibility that our instruments may be isolating misspecifications rather than correcting for measurement error is to compare the estimates of β_T as we restrict the sample in a way that should reduce the degree of any specification error. Within the structure of the random growth specification of earnings, our ability to distinguish transitory from permanent income changes depends in part on the length of the panel of earnings data for each household. As noted above, we require that a household participated in at least three *AHS* surveys to be included in our sample. Raising that hurdle narrows the estimation sample, but increases the average panel length used to isolate the transitory income component. Thus, if our IV strategy predominantly is picking up specification error rather than correcting for measurement error, the estimate of β_T should decrease when we raise the minimum panel length. However, when we double the minimum panel length from 3 to 6 surveys (which reduces the sample size to 5,164), we find that the IV estimate of the transitory income elasticity of maintenance expenditures actually increases slightly. Thus, our robustness check does not provide any indication that our IV strategy is inadvertently picking up specification error instead of correcting for measurement error.

5 Conclusion

The last 25 years has witnessed a significant rise in transitory income variance in the United States. Browning and Crossley (1999) argue that households can use durable goods to help smooth nondurable consumption via an internal capital market. When households face a transitory income decline, they postpone the replacement of goods such as clothing. This delay creates only a second-order decline in the consumption flow from these durables. The delay, though, generates cash flow that the household

[26] The increase in the overall income elasticity from the OLS to the IV estimate reported in Table 2 is less than what would be predicted based on the degree of measurement error in reported earnings documented by Bound and Krueger (1991).

can use to maintain their consumption of nondurables. This has a first-order impact on the household's utility.

In this paper, we investigate the extent to which homeowners use the maintenance decision on their homes in a similar fashion to help them smooth their nondurable consumption in the face of transitory income fluctuations. Homes are the most significant durable asset in the typical household's portfolio, and annual maintenance expenditures are around $2,100. By varying the timing of these home maintenance decision, the household can generate cash flow to help finance nondurable consumption.

Using *AHS* data, we find that households do adjust their home maintenance expenditures in response to household income changes. Using our estimate of the transitory component of these income changes, we corroborate the finding by Dynarski and Gruber (1997) of a positive elasticity of homeowner maintenance decisions to income variation. This finding is supportive of the view that homeowners adjust their maintenance expenditures in their efforts to smooth consumption. However, this conclusion needs to be tempered by the recognition that decomposing income changes into their transitory and permanent components is a difficult exercise and one where we can not fully verify the degree of our success. In addition, conditional on our estimated decomposition, the economic significance of this smoothing method appears to be limited in practice, as it is comparable to the adjustment of clothing expenditures. This mechanism also complements the consumption smoothing homeowners can achieve by adjusting the debt position in their house as documented in Hurst and Stafford (2004).

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Data Appendix

The Bureau of Economic Analysis (BEA) Regional Economic Information System (REIS) provides personal income and earnings on a MSA/PMSA level of aggregation. As an instrument, we take the average earnings per job of each Metropolitan Statistical Area (MSA) or Primary Metropolitan Statistical Area (PMSA) in the *American Housing Survey* (*AHS*) sample.

The current data available through REIS have been re-aggregated to the most recent county-based geographic definitions of Metropolitan and Micropolitan Statistical Areas, which were derived by the White House Office of Management and Budget from the results of the 2000 Census (OMB Bulletin No. 03-04). These geographic boundaries are often similar, but do not match those used in the *AHS* sample. The BEA continues to publish an older REIS database which is based on the previous vintage of MSA/PMSA concepts. This database is available by request on CD-ROM from the BEA.

Our sample from the *AHS* includes 114 MSA/PMSA areas. Of the 114, we are able to exactly match 105 with the REIS data. The REIS database replaces MSA/PMSA areas with their New England County Metropolitan Areas (NECMA) when applicable. Of the nine unmatched areas, we matched four to their NECMA analogues. While these are not exact matches to the original MSA/PMSA, they are very close in geography.

MSA/PMSA to NECMA Mapping

MSA/PMSA	**NECMA**
Boston, MA-NH PMSA (1120)	Boston-Worcester-Lawrence-Lowell-Brockton, MA-NH NECMA (1123)
Hartford, CT MSA (3280)	Hartford, CT NECMA (3283)
Providence-Fall River-Warwick, RI-MA MSA (6480)	Providence-Warwick-Pawtucket, RI NECMA (6483)
Springfield, MA MSA (8000)	Springfield, MA NECMA (8003)

Four other unmatched areas from the *AHS* sample were matched to the closest CBSA (the new county-based Metropolitan and Micropolitan Statistical Area definitions) from the current REIS database. These are also very close in geography, but their boundaries will be slightly bigger because as a county-based system, they include entire counties, whereas the MSA/PMSA definition included only partial counties.

MSA/PMSA to CBSA Mapping

MSA/PMSA	CBSA
Bridgeport, CT PMSA (1160)	Bridgeport-Stamford-Norwalk, CT CBSA (14860)
Stamford-Norwalk, CT PMSA (8040)	
New Haven-Meriden, CT PMSA (5480)	New Haven-Milford, CT CBSA (35300)
Worcester, MA-CT PMSA (9240)	Worcester, MA (49340)

The data for the last unmatched area, Lawrence, MA PMSA, were constructed as an employment weighted composite of county level data for Essex County, MA and Rockingham County, NH, using county level data available in REIS. This is very close to the original PMSA definition which included most of these two counties.

Table 1. Repair / maintenance / improvement expenditures

Category	Probability of positive expenditure, Pr($>0)	Conditional expenditure, E($\|$>0)	Unconditional expenditure, E($)
Routine maintenance	0.77	1,482	1,149
New addition	0.04	6,224	272
New/remodeled kitchen	0.10	3,972	406
New/remodeled bath	0.12	2,289	286
Roof	0.16	2,610	410
Siding	0.05	3,478	173
New insulation; storm doors/windows	0.20	1,569	319
Major equipment	0.13	2,485	322
Other, > $500 each	0.25	3,002	765
Aggregate	0.90	4,557	4,102

Notes: *AHS* data, 1985-1993, real 1998 expenditures over two year periods.

Table 2. Aggregate maintenance / improvement expenditures

	OLS		IV	
2-year change in log earnings[a]	0.424**		0.471**	
	(0.079)		(0.082)	
2-year change in permanent log earnings		0.617**		0.630**
		(0.147)		(0.148)
2-year change in transitory log earnings[b]		0.384**		0.412**
		(0.082)		(0.085)
Lag 1st year in house	−1.654**	−1.658**	−1.655**	−1.658**
	(0.163)	(0.163)	(0.163)	(0.163)
Age of household head	−0.001	−0.001	−0.001	−0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Change in household size	0.063	0.065	0.060	0.063
	(0.046)	(0.046)	(0.047)	(0.046)
Become married	−0.033	−0.135	−0.043	−0.134
	(0.177)	(0.187)	(0.177)	(0.187)
Become single	−0.133	−0.026	−0.118	−0.024
	(0.235)	(0.244)	(0.235)	(0.244)
SMSA house price appreciation (2-year rate)	0.023	0.027	0.020	0.024
	(0.362)	(0.363)	(0.362)	(0.363)
Neighborhood improved	−0.201**	−0.200**	−0.201**	−0.199**
	(0.099)	(0.099)	(0.099)	(0.099)
Neighborhood declined	0.118	0.121	0.118	0.121
	(0.098)	(0.098)	(0.098)	(0.098)

Notes: *AHS* data 1985-1993. Sample size 10,442. Standard errors are given in parentheses and have been adjusted for any dependence between households in the same SMSA and year. The specifications include year and region effects. Instruments for the change in earnings are indicators for 2-year changes in the deciles of the income distribution in the household's major census region.

[a] Instruments for the change in log earnings include decile indicators for changes in log earnings in the household's major Census region and year, the average change in log earnings in the AHS sample in the household's SMSA and year, and the change in the log earnings per worker in the household's SMSA and year from the *REIS* data.

[b] Instruments for the change in log transitory earnings include quintile indicators for changes in log transitory earnings in the household's major Census region and year, the average change in log transitory earnings in the *AHS* sample in the household's SMSA and year, and the change in the residual log earnings per worker in the household's SMSA and year from the *REIS* data.

** significant at the 5% level, * significant at the 10% level

Table 3. Aggregate maintenance / improvement expenditures, by age of head

Sample	Other	Recent 1st-time buyer, no refinance
a) age 20 – 39, liquidity constrained=26.7%[a] [n=3,708]		
2-year change in log earnings	0.587**	0.553**
	(0.180)	(0.274)
2-year change in permanent log earnings	0.625**	1.111**
	(0.320)	(0.324)
2-year change in transitory log earnings	0.465**	0.350
	(0.178)	(0.304)
b) age 40+, [n=6,494][b]		
2-year change in log earnings	0.435**	
	(0.095)	
2-year change in permanent log earnings	0.502**	
	(0.180)	
2-year change in transitory log earnings	0.392**	
	(0.104)	

Notes: AHS data 1985-1993. IV estimates reported. Standard errors are given in parentheses and have been adjusted for any dependence between households in the same SMSA and year. The specifications include year and region effects. Instrument sets are the same as described in the notes of Table 2.

[a] Define liquidity constrained to mean a first-time homebuyer within five years of the purchase who has not completed a cash-out refinance of his/her mortgage.

[b] Because of the very small sample of recent first-time homebuyers among older households, we exclude them from the estimation.

Table 4. Transitory Income Elasticities by specific maintenance / improvement categories

Misc maintenance	0.215**
	(0.096)
New addition	0.187**
	(0.051)
New / remodeled kitchen	0.202**
	(0.064)
New / remodeled bath	0.104
	(0.065)
Roof	0.000
	(0.100)
Siding	0.015
	(0.050)
New insulation; storm doors/windows	0.169**
	(0.082)
Major equipment	0.157**
	(0.075)
Other > $500 each	0.087
	(0.098)

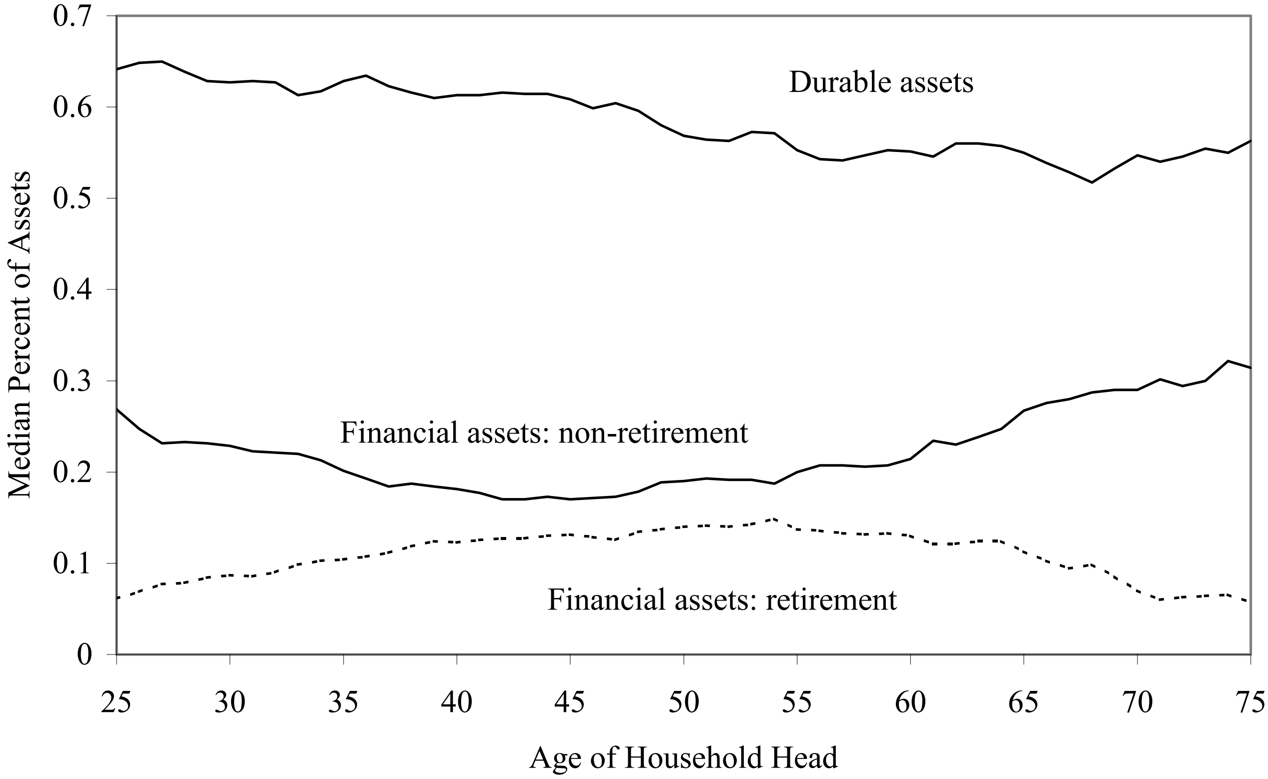
Notes: *AHS* data 1985-1993. Sample size 10,442. See equation (7) in the text for details on the construction of the elasticity. Standard errors are given in parentheses and have been adjusted for any dependence between households in the same SMSA and year. Specification includes year and region (4) effects.
** significant at the 5% level, * significant at the 10% level

Appendix Table A1. Data Sources and Summary Statistics

Variable	Source	Mean	Standard Deviation	Min	Max
2-year change in transitory residual log earnings	AHS: ZINC (#0621, pg. 112)	−0.005	0.42	−2.98	2.96
Age of household head	AHS: AGEMID (#0490, pg. 98)	43.38	8.45	22	59
White	AHS: RACE (#0521, pg. 100)	0.81	0.39	0	1
Male	AHS: SEX (#0553, pg. 101)	0.80	0.40	0	1
High School Graduate	AHS: GRADE1 (#0568, pg. 102)	0.31	0.46	0	1
Some College	AHS: GRADE1 (#0568, pg. 102)	0.23	0.42	0	1
College Graduate	AHS: GRADE1 (#0568, pg. 102)	0.20	0.40	0	1
Graduate School	AHS: GRADE1 (#0568, pg. 102)	0.19	0.39	0	1
Change in household size	AHS: PER (#0586, pg. 104)	−0.03	0.78	−7	7
Married	AHS: MAR (#0506, pg. 100)	0.77	0.42	0	1
Become married	AHS: MAR (#0506, pg. 100)	0.03	0.17	0	1
Become single	AHS: MAR (#0506, pg. 100)	0.03	0.17	0	1
Lag 1st year in house	AHS: BUYYR (#1081, pg. 153) YEAR (#1520, pg. 201)	−0.06	0.25	−1	0
Recent 1st time buyer, no cash- out refinance	AHS: FRSTHO (#0029, pg. 33) YRMOR (#1104, pg. 156) AHS: AMMORT (#1101, pg. 155)	0.14	0.35	0	1
SMSA house price appreciation, 2-year	Freddie Mac: http://www.freddiemac.com/finance/cmhpi/	0.09	0.13	−0.17	0.69
Neighborhood improved	AHS: HOWN (#0291, pg. 78)	0.12	0.33	0	1
Neighborhood declined	AHS: HOWN (#0291, pg. 78)	0.15	0.36	0	1
Avg change in log earnings in SMSA/year	AHS	−0.01	0.13	−1.00	1.01
Avg change in log transitory earning in SMSA/year	AHS	−0.02	0.11	−0.99	1.12
Change in log real other income	AHS	0.47	4.45	−11.61	11.46
Change in SMSA log real earnings/worker	REIS	0.01	0.03	−0.12	0.12
Change in SMSA transitory log real earnings/worker	REIS	0.00	0.02	−0.13	0.09

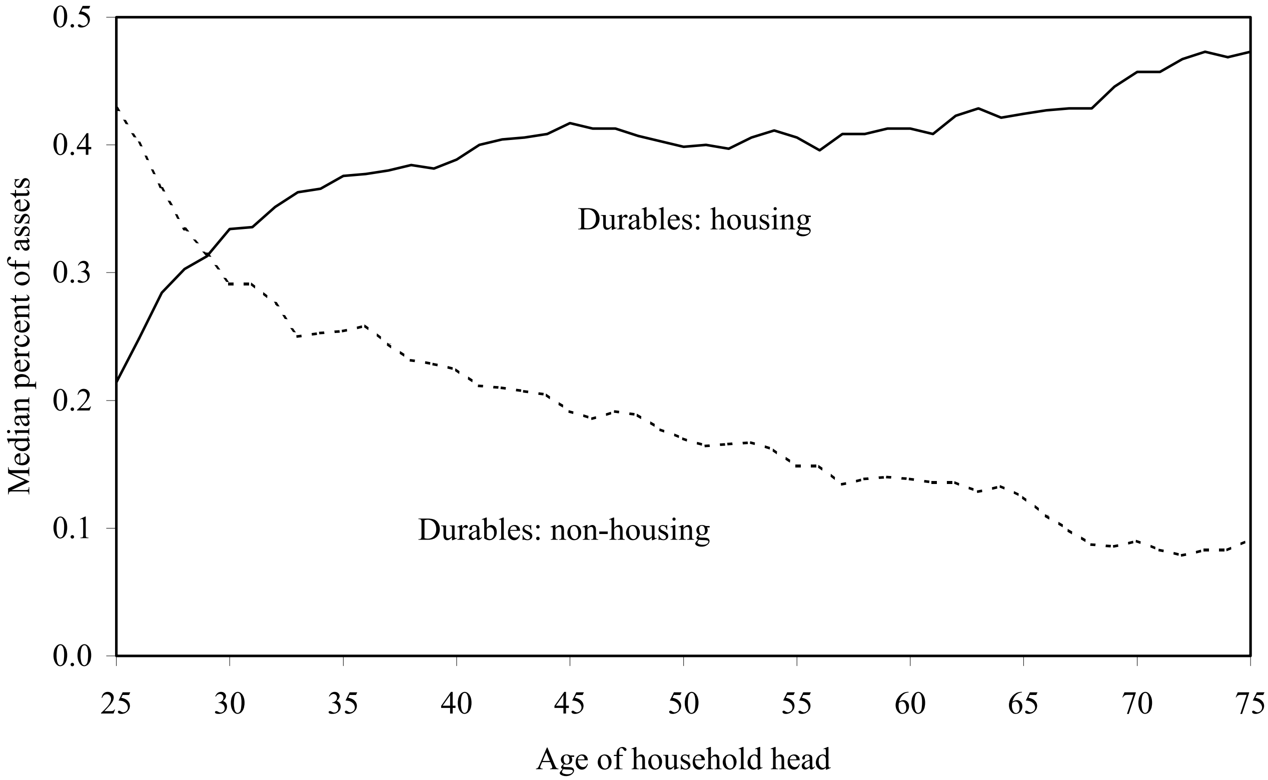
Notes: For *AHS* variables, the source column lists the AHS variable *name*, reference number, and the page from the 1990 edition codebook.

Figure 1. Household Asset Allocation by Age



Source: Survey of Consumer Finance, 2001. Smoothed median age-specific asset shares are reported. Durables include housing, cars, furniture, art, jewelry, and collectibles. Non-retirement financial assets include cash, checking and savings accounts, CDs, saving bonds, mutual funds, stocks, and bonds.

Figure 2. Household Durable Assets by Age



Source: Survey of Consumer Finances, 2001. Smoothed age-specific median asset shares. See notes for Figure 1 for description of non-housing durable assets.

Figure 3. Friction Model Illustration