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ABSTRACT

House Prices and Risk Sharing*

Using data from the Panel Study of Income Dynamics, we show that homeowners are able to maintain a high level of consumption following job loss (or disability) in periods of rising local house prices while the consumption drop for homeowners who lose their job in times of lower house prices is substantial. The results are consistent with homeowners being able to access wealth gains when housing appreciates as witnessed by their ability to smooth consumption more than renters. We calibrate and simulate a model of endogenous homeownership and consumption which is able to reproduce the patterns in the data quite well.

JEL Classification: D12 and E21
Keywords: consumption smoothing, psid and regional house prices

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or "risk sharing." Risk sharing is interesting per se and focusing on risk sharing allows us to abstract from a host of difficult-to-control-for aggregate variables that may affect consumption. Our main contribution is to study how risk sharing varies with house prices by matching PSID data and house price data at the metropolitan level from the FHFA. We focus on house-price *appreciation* which provides exogenous shocks to homeowners' wealth and collateral.[3] We find that homeowners maintain relatively higher (lower) levels of nondurable consumption after job displacement or disability when house values increase (decrease).

To interpret our findings, we calibrate and simulate a life-cycle model of households with preferences for housing (shelter) and nondurable consumption. The model captures the main features of homeownership—in particular the role of housing as both a consumption good and an asset: homeownership is endogenous in our model where housing services can be obtained either in the rental market or through homeownership. Households adjust (nondurable, non-housing) consumption, and possibly housing, in response to (exogenous) income fluctuations although buying or selling a house requires paying a proportional commission which makes the effect of house price shocks on nondurable consumption more complicated than the effect of liquid wealth shocks, such as winning the lottery. For homeowners with housing equity above a minimum down payment a positive capital gain in housing is fully liquid—although the household may choose to upgrade to a larger house while paying a proportional commission. Homeowners who own less than the minimum down payment will only be able to access capital gains in housing if it pushes their equity above the required minimum. In the face of a persistent negative shock to housing, a homeowner may choose to pay the commission and downsize or move to rental housing—in particular, if the shock happens at the same time as a persistent income loss.

[3] The PSID has information on household house equity, but these data are questionable for our purpose, because household-level equity is likely to be endogenous.

We perform panel-data regressions on simulated data in the same fashion as we estimate our empirical relations using real data. We compare the estimated parameters from the data and from model simulations, and—to the degree that magnitudes match between actual and simulated data—interpret our empirical findings. Our simulations show that homeowners maintain consumption better than renters when the relative price of housing increases.

Our model leaves out many real-world complications; nonetheless, we find that the predictions of the model match the results from the PSID well. We do not attempt to structurally fit our model, as in Li, Liu and Yao (2009), who have a different focus but use a model similar to ours. The disadvantage of our approach, compared with a structural approach, is that we cannot test the model, and we discuss mainly the quantitative predictions regarding the impact of the shocks that match our empirical focus. The advantage is that our findings are robust to many forms of model misspecification.

Our empirical approach is related to work that has attempted to measure the direct impact of house values on consumption—typically under the label of "wealth effects" of house-price changes. Because national house prices correlate with economic conditions in general, the quantification of the effect of house prices on consumption remains controversial. The most promising avenue seems to be regressions that rely on regional house prices as pioneered by Attanasio and Weber (1994)—such regressions allow the authors to control for nationwide effects. Further, these authors simulate a theoretical model to evaluate the plausibility of their empirical estimates. Two papers in that vein are Campbell and Cocco (2007), who find evidence of a wealth effect, and Attanasio, Blow, Hamilton and Leicester (2009), who argue that common causality is a more likely explanation for the patterns of consumption and house-price growth in the United Kingdom. Like these authors, we use regional house prices, compare renters to owners, and, more briefly, young households to old households.

Another paper of particular relevance is Hurst and Stafford (2004), who document that house equity is used as a mechanism to smooth income shocks due to unemployment. This work complements ours, because their empirical focus is on the decision to refinance while our work directly considers consumption. Our work is also related to Lustig and Van Nieuwerburgh (2010) who find there is more risk sharing between U.S. metropolitan areas in periods when average U.S. house-price appreciation is high.[4] Our paper is related to Chetty and Szeidl (2007) who study consumption patterns when a part of wealth is "committed" and cannot be easily adjusted as is the case for our consumers in the sense that it is costly to adjust housing consumption. Finally, Leth-Petersen (2010) considers the effect of increasing the ability to use housing as collateral by studying the effect of an exogenous relaxation of home-equity lending restrictions in Denmark.

We explain our empirical strategy in Section 2 and describe the data and report empirical estimation results in Section 3. We present our theoretical model and its implications in Section 4 and report the results of regressions using simulated data in Section 5. Section 6 concludes.

2. Regression specification

In an endowment economy with one nondurable good, complete Arrow-Debreu markets and constant relative risk aversion utility, all consumers will have identical consumption growth rates. Mace (1991) tested this prediction in a panel-data regression of consumption on income with controls for aggregate effects while Cochrane (1991) examined whether consumers are fully hedged against job loss. Let $z_{it} = \log Z_{it} - \log Z_{it-4}$ be the growth

[4] Lustig and Van Nieuwerburgh (2010) consider the role of housing collateral in a general equilibrium model with state-contingent claims. However, they do not consider renters versus homeowners, and they use U.S.-regional data.

rate of a generic variable Z, such as consumption C, of individual i from year $t-4$ to t, and let $\bar{z}_t$ be the period t specific mean of any generic variable z. Let hp_{mt} be the four-year growth rate of house prices in the metropolitan area m where individual i lives and let D_{it} be a dummy taking the value 1 if the head of household i suffers displacement and 0 otherwise. Alternatively, D_{it} is an indicator that takes the value 1 at the onset of disability, –1 if the household head exits from disability, and 0 otherwise. Pooling data from regions with different house-price appreciation, we examine the impact of job loss (disability) on consumption and the risk-sharing role of housing in the face of job displacement (disability) by estimating the relation:

$$
\begin{aligned}
c_{it} - \bar{c}_t =& \mu + \beta\ (hp_{mt} - \overline{hp}_t) + \xi\ (D_{it} - \bar{D}_t) \\
& + \zeta\ (D_{it} - \bar{D}_t) \times (hp_{mt} - \overline{hp}_t) + (X_{it} - \bar{X}_t)'\delta + \varepsilon_{it}\,, \qquad (1)
\end{aligned}
$$

where X_{it} is a vector of controls (age, the square of age, and family size). We subtract the time-specific mean from all variables because the subtraction of the aggregate non-diversifiable component gives all estimated coefficients the interpretation of showing deviations from perfect risk sharing; in particular by subtracting $\overline{hp}_t$ from hp_{mt}, we remove the nationwide average house-price appreciation from the time-varying coefficient—the time-series variation in average house prices is likely correlated with other aggregate variables, such as stock market performance, and we want to hedge against house prices capturing such variables. Here, the derivative of idiosyncratic consumption growth with respect to a disability (displacement) shock is $\xi + \zeta(hp_{mt} - \overline{hp}_t)$, which would be 0 under perfect risk sharing. When these coefficients are not 0, a positive coefficient of ζ implies that house-price appreciation dampens the effect of displacement on consumption growth—that is, risk sharing goes up with house-price appreciation. Our regressions are similar to those estimated by Cochrane (1991) with a house-price interaction added.[5] Briefly, under full insurance of nondurable consumption and housing services, deviations of idiosyncratic consumption growth from the nationwide average should be orthogonal to the deviation of an idiosyncratic shock-to-income (such as disability or displacement) from the nationwide average, as well as its interaction with regional house-price growth, assuming house prices are uncorrelated with measurement error in consumption and shocks to the relative taste for consumption of nondurables and housing services. That is, under the null of full insurance, the coefficients β, ξ, and ζ should be equal to zero. If, however, the risks to nondurable consumption are shared nationally but the risks to consumption of housing services are shared within a region, only $\hat{\xi}$ and $\hat{\zeta}$ should be statistically indistinguishable from zero.[6] See Appendix A for derivation of equation (1).

3. Empirical estimations

3.1. Data

We use individual- and household-level data from the PSID, which is a longitudinal study of U.S. households. We will briefly describe our estimation sample; for more details on sample selection see Appendix B.

The PSID maintains Geocode Match Files, which contain the identifiers necessary to link the main PSID data to Census data which allows us to add data on characteristics of each respondent's neighborhood to the already rich array of socioeconomic variables

[5]Cochrane (1991) estimated cross-sectional regressions, but panel data regressions with time fixed effects can be seen as weighted averages of the results of cross-sections. Cochrane's definition of involuntary job-loss is essentially the same as our definition of "displaced" and our regressions confirm his results. (Cochrane (1991) also leaves out income).

[6]We also, more briefly, include income growth in our regressions. Income growth is more likely to be endogenous to shocks to desired consumption or correlated with left-out regressors and we therefore choose to first present results without income included. However, we want to verify that our results are robust to the inclusion of income because income is obviously correlated with displacement and job loss.

collected in the PSID.[7] We match households to their MSA of residence and use house-price appreciation at the metropolitan level.

As a measure of consumption we use food consumption because of a lack of broader consumption aggregate, although we also show results for imputed nondurable consumption. Food consumption consists of food consumed at home and away from home (excluding food purchased at work or school). For household income, we use the sum of real labor and transfer income of head and wife before taxes. We deflate food consumption at home and away from home, and household income by the all-items-less-housing consumer price index (CPI) from the Bureau of Labor Statistics.

We consider a household head to be displaced if the head's "previous company folded or changed hands or moved out of town; employer died, went out of business," because of "strike, lockout," or because the head was "laid off/fired."[8] The disability variable is constructed from two questions typically referred to as "limiting conditions."[9] The first asks: Do "you (head) have any physical or nervous condition that limits the type of work or amount of work you can do?" The second question asks: "How much does it limit your work?" We assume the head is disabled if he or she answers yes to the first question and states "can do nothing " or indicates disability limits the ability to work somewhat or a lot.

Because PSID data (in particular, food consumption) are noisy at the annual frequency, we use four-year (overlapping) growth rates. This choice reduces measurement error and averages out temporary fluctuations in income and consumption. Economists typically agree that longer-lasting ("permanent") shocks matter more for welfare, so little

[7]The Geocode Match data are highly sensitive (usually pinpointing the census tract in which families live), and are available only under special contractual conditions designed to protect the anonymity of respondents.

[8]The PSID did not collect information on displacement during the 1994–1997 waves.

[9]In 1973, 1974, and 1975, only new heads were asked these questions. In cases where the answer in one of those years is missing, we impute it using the answer from a preceding year.

is lost by looking at the longer frequencies where permanent shocks are relatively more important.[10]

In our growth regressions, the disability variable enters as 0 if there was no change in the disability status from period $t-4$ to t, as 1 if the head reports disability at t but not at $t-4$, and as -1 if the head reports disability at $t-4$ but not at t. The displacement variable enters as 1 if the head reports being displaced in year $t-3$, $t-2$, $t-1$, or t. When presenting results by housing tenure status, we define a homeowner as a household that owned a house in all periods involved in calculating the consumption growth rate, and analogously for renters.

We restrict our analysis to families with stable composition (same head and wife during the four-year span), whose head of household is of prime age (25–65) and families for which we have information on housing status and region of residence during the four-year span. Our data exclude the Latino and Immigrant samples of the PSID, but include households from both the representative core sample and the Survey of Economic Opportunities (SEO), the sub-sample of low income households. We also restrict our sample to households that reside in the same metropolitan area during a given four-year period so we can meaningfully assign to them four-year MSA house-price changes.

House-price appreciation. We use house-price indices at the MSA level published by the FHFA, which reports quarterly house-price indices for single-family detached properties. The agency bases these reports on data on conventional conforming mortgage transactions obtained from the Federal Home Loan Mortgage Corporation (Freddie Mac) and the Federal National Mortgage Association (Fannie Mae). The house-price indices are based on the methodology proposed by Case and Shiller (1989).[11] We use metro-level house

[10]Cochrane (1991) used three-year growth rates, similar to our frequency. We choose an even number of years to match up with the biennial sampling frequency initiated by the PSID in 1997.

[11]The index for each geographic area is estimated using repeated observations of housing values for individual single-family residential properties on which at least two mortgages were purchased or securitized

prices which can be assumed to be exogenous for individual households and deflate house indices by the all-items-less-housing CPI.

When merging FHFA house-price indices with PSID data, we end up with a sample that covers the period 1976–2005. The overall mean (four-year) house-price appreciation is 6 percent, with a 19 percent standard deviation while median house-price appreciation is lower at 4 percent. There is rich variation across MSAs and over time during this period. Three of the MSAs with the lowest house-price appreciation during the period are Binghamton, Houston, and New Orleans, which have a mean (standard deviation) appreciation of –7.7 (13.5), –5.7 (14.5), and –3.3 (13.4) percent, respectively. Three of the MSAs with the highest house-price appreciation are Boston, San Francisco, and the New York City area, at 15.3 (28.2), 14.7 (22.9), and 11.5 (24.5), respectively. See Appendix C for more details.

3.2. Estimation results

We estimate the regressions described in Section 2. We use a two-stage Prais-Winsten GLS procedure, which is efficient in the case of first-order autocorrelation; our observations are overlapping and therefore, by construction, autocorrelated.[12] The standard errors are calculated using robust clustering at the MSA level.

The range of four-year log differences of consumption is between –1.8 and 1.7, while that of income is even larger. House prices also show large deviations from the U.S. mean. On average, about 12 percent of the sample receives a displacement shock during a four-year time span, while 5 percent suffers from a limiting condition and 3 percent recovers from one—see (appendix) Table A-1.

Table 1 shows results for owners, renters, and the pooled sample. We first consider

by either Freddie Mac or Fannie Mae since January 1975.

[12]Our data will have autocorrelation of order higher than one, but typically most efficiency gains are obtained as long as first-order correlation is allowed for.

disability and displacement separately and then combine those events into a variable we call "bad news." Bad news is a dummy variable that equals one if a household head becomes either displaced or disabled (or both). The results for homeowners in columns (1) and (2) indicate that the main effect of disability or displacement is similar with a drop in nondurable consumption of about 4 percent. The direct impact of house-price appreciation is robustly estimated at about 14 percent for owners. The interaction of house prices with disability is very large, estimated at about 0.33, while the interaction with displacement is about 0.16. In the regression using bad news—column (3)—the main effect of bad news is –0.05 while the interaction term is 0.18. These numbers imply that nondurable consumption drops by about 5 percent when the household head becomes disabled or displaced in the absence of house-price appreciation but if house prices appreciate by 10 percent over the relevant four-year span, the drop in nondurable consumption is only about 3 percent (ignoring the main effect of house-price appreciation).

For renters, we find a large direct effect of house prices which likely is due to house prices being correlated with components of income or with expectations of future income. The interaction of disability and displacement with house-price growth is negative for renters with a larger (although insignificant) coefficient for disability. The direct effect of disability is estimated at –0.06, and the direct effect of displacement at –0.08. Combining these into bad news we find a coefficient of –0.07 while the interaction term becomes very close to 0—the variable "bad news" delivers less noisy results and, in the following, we use this variable only. The last column shows the results for a combined sample of owners and renters; the results are in-between those found for each of these samples.

Table 2 explores different samples and specifications in order to explore robustness and add to our understanding. We only present the direct effects of house price growth, bad news, and their interaction to conserve space. The table includes a column for owners and one for renters and, for convenience, repeats the results of Table 1 as the first entry. The second entry limits the sample to households that did not move during each four-year period. This addresses the issue of whether households free up home equity by downsizing their residence after being hit by a bad news shock. However, the results are similar to the baseline case and the insurance effect of house price appreciation is therefore not mainly a result of downsizing. Next, we explore if the results are robust to using non-overlapping intervals. The results are similar although the interaction terms are large for both owners and renters, although not significant for renters. The non-overlapping regressions are clearly estimated with less precision.

The large coefficient to house-price appreciation for renters is puzzling. Household income may contain a regional component correlating with house-price growth and we attempted to extract the component of house-price appreciation orthogonal to income by regressing house-price appreciation on average income growth in the MSA and using the residuals as our measure of house-price appreciation.[13] This lowers the estimated coefficient to house price appreciation slightly for renters but does not change the coefficients to any variable strongly. These results highlight how careful one needs to be in interpreting aggregate correlations between appreciation of house values and nondurable consumption as causal. The next two sets of results consider young and old households, respectively. Young renters have consumption that reacts positively to house-price appreciation which would be consistent with a correlation of house-price appreciation with income expectations. The interaction term is insignificant for young owners as well as renters. Older individuals are hit harder by bad news. Old owners and, in particular, old renters react less strongly to house price appreciation while the interaction term is highly significant for older owners only. The latter result is likely reflecting that older homeowners, on average,

[13]MSA income is per capita real income received by all persons from all sources and is available from the Bureau of Economic Analysis.

have a larger amount of accumulated housing equity that helps them insure nondurable consumption.

The interaction effect may be due to changes in house prices tightening or loosening credit constraints. We expect poorer households to be subject to tighter credit constraints and examine if households in the SEO sample, the subsample of low-income households, have larger interaction terms than individuals in the representative core sample. We find a tendency for the interaction term to be larger for the SEO sample but the difference is not quite statistically significant.

We next, in the top two panels of Table 3 explore differences between food at home versus food at restaurants ("food away"). Food away is very elastic and reacts strongly to bad news and, maybe surprisingly, food away does not react significantly to house prices and the interaction term is insignificant. Food at home reacts less strongly, but still significantly to bad news while there is quite a strong effect of house-price appreciation. The interaction term is large and significant for owners for food at home indicating that the insurance effect of rising house prices predominantly works through this component of food consumption. In Appendix D, we report very similar results to the baseline case when using a measure of imputed nondurable consumption based on the methodology of Blundell, Pistaferri and Preston (2008).

In Table 3, we further show two sets of results for the sample split into an early period 1980–1994 and a late period 1994–2005.[14] This split gives us a similar number of observations in different subsamples. If financial liberalization and higher use of home equity lines of credit made housing equity easier to access one would expect to find that

[14]We use the disability indicator instead of bad news since information on disability was collected consistently throughout our sample period, while information on displacement, used for constructing the bad news indicator, was not collected during 1994–1997. The results using bad news instead are qualitatively similar: for the 1980–1994 sample the interaction term is estimated at about 0.19, significant at the 5% level, while the interaction term for the 1994–2005 sample is about 0.20, nearly significant at the 10% level.

house price increases would provide more consumption insurance in the latter sample. However, the results are very robust to the sample period. Likely, people with liquid life-cycle savings were able to draw on those in the early sample, possibly taking out a second mortgage.

Finally, we control for income in the bottom panel of Table 3. As expected the coefficient to bad news becomes slightly smaller because part of the impact is captured by income, but the reduction is not large—likely because income shocks are partly transitory and partly persistent while our bad news shocks are overwhelmingly persistent and not well captured by measured income. In Appendix E, we show that using self-reported housing equity (the difference between self-reported house value and the value of remaining mortgages and home equity loans) rather than house-price appreciation in equations with house equity substituted for house-price appreciation results in very small, clearly insignificant coefficients for both the direct effect and the interaction. Those results suggest that house prices do not simply capture the level of housing wealth, and also validate our point that using exogenous house-price changes is more robust than relying on endogenous home equity numbers which may be contaminated by preference heterogeneity, etc. [15]

4. The model and calibration

To interpret our results, we introduce a model and perform regressions using simulated data of the same form as those performed with PSID data. An important feature of our

[15] In a previous version of the paper, we explored if our results were capturing differences in household liquid wealth by splitting our sample by financial assets. The interactions of displacement and disability with house-price growth were found insignificant for renters of all wealth levels which indicates that the house-price variable is not standing in for differences in wealth. Those results were based on a limited sample because the PSID started collecting wealth data only in 1984, available at 5-year intervals up to 1999, and biennially afterwards. Our sample requirement of household stability further limits the ability of getting reliable results using wealth data and we, therefore, chose not to report those results.

model is that we explicitly consider homeownership as a choice for households (i.e., an endogenous tenure choice). We follow Díaz and Luengo-Prado (2008) and consider a life-cycle model where households derive utility from consumption of a nondurable good and housing services that can be obtained in a rental market or through homeownership. House buyers pay a down payment, buyers and sellers pay transactions costs, and housing equity above the amount of the down payment can be used as collateral for loans. There are no other forms of credit. Tax treatment of owner-occupied housing is preferential as in the United States. Households face uninsurable earnings risk and uncertainty arising from house-price variation.

4.1. The model

Preferences, endowments, and demography. Households live for up to T periods and face an exogenous probability of dying each period. During the first R periods of life they receive stochastic labor earnings and from period R on, they receive a pension. When a household dies, it is replaced by a newborn and its wealth is passed on as an accidental bequest. Houses are liquidated at death; thus, newborns receive only liquid assets.

Households derive utility from nondurable goods and from housing services obtained from either renting or owning a home. One unit of housing stock provides one unit of housing services. The per-period utility of an individual of age t born in period 0 is $U(C_t, J_t)$ where C stands for nondurable consumption and J denotes housing services. Households cannot rent and own a home at the same time. The expected lifetime utility of a household born in period 0 is $E_0 \sum_{t=0}^{T} \frac{1}{(1+\rho)^t} \zeta_t U(C_t, J_t)$, where $\rho \geq 0$ is the time discount rate and ζ_t is the probability of being alive at age t.

Market arrangements. A household starts any given period t with a stock of residential assets, $H_{t-1} \geq 0$, deposits, $A_{t-1} \geq 0$, and collateral debt (mortgage debt and home-equity loans), $M_{t-1} \geq 0$. Deposits earn a return r^a and the interest on debt is r^m. Households buy the house that renders services in period t at the beginning of the period. The price of one unit of housing stock in period t (in terms of nondurable consumption) is q_t, while the rental price of one unit of housing stock is r_t^f.

When buying a house households must make a down payment, $\theta q_t H_t$.[16] This means that a new mortgage must satisfy the condition: $M_t \leq (1-\theta)\, q_t\, H_t$. For homeowners who do not move in a given period, houses serve as collateral for loans (home-equity loans) with a maximum loan-to-value ratio (LTV) of $(1-\theta)$. If house prices go down, a homeowner can simply service debt if he or she is not moving; i.e, as long as the homeowner stays in the same house, M_t could be higher than $(1-\theta)\, q_t\, H_t$ as long as $M_t < M_{t-1}$. Foreclosure is not allowed so a homeowner can be "upside-down" (have negative housing equity) for as many periods as the household desires.[17]

Households pay a fraction κ of the house value when buying a house (e.g., sales tax or search costs). When selling a house, a homeowner loses a fraction χ of the house value (brokerage fees). Houses depreciate at the rate δ^h and households can choose the degree of maintenance. Buying and selling costs are paid if $|H_t/H_{t-1} - 1| > 0.05$ which indicates that only homeowners upsizing or downsizing housing services by more than 5 percent pay adjustment costs.[18]

[16] We abstract from income requirements for people purchasing houses. Many lenders follow the rule of thumb of "three times income" in determining the size of mortgages. However, the empirical literature finds that wealth constraints are more important than income constraints when people purchase a home. See, for example, Linneman, Megbolugbe, Watcher and Cho (1997) or Quercia, McCarthy and Watcher (2000).

[17] These assumptions simplify the computation of the model while allowing us to consider both down-payment requirements and home-equity loans without modeling specific mortgage contracts or mortgage choice. See Li and Yao (2007) for an alternative model with refinancing costs, and Campbell and Cocco (2003) for a discussion of optimal mortgage choice.

[18] Results are robust to alternative formulations of the adjustment costs such as pure maintenance or pure depreciation. Our specification, which is in-between the two, is slightly easier to implement computationally with a discrete grid.

Households sell their houses for various reasons. First, households may want to increase or downsize housing consumption throughout the life cycle. Second, selling the house is the only way to realize capital gains beyond the maximum LTV for home-equity loans so households may sell the house to prop up nondurable consumption after depleting their deposits and maxing out home-equity loans. Third, households may also be forced to sell their houses as they are subject to an idiosyncratic moving shock, z_t. This shock is meant to capture the effect of "geographical" mobility stemming from job change and demographic shocks not modeled for simplicity.

The government. The government taxes income, Y, at the rate τ_y. Interest payments on mortgages and home-equity loans are deductible from the income base. The deduction percentage is denoted τ_m. Imputed housing rents for homeowners are tax-free so taxable income in period t is $Y_t^\tau = Y_t - \tau_m \, r^m \, M_{t-1}$. Proceeds from taxation finance government expenditures that do not affect individuals at the margin.

Earnings and house-price uncertainty. Households are subject to household-specific risk in labor earnings and house-price risk common to residents of the same region. For working-age households, labor earnings, W_t, are the product of permanent income and transitory shocks (P_t, ν_t and ϕ_t, respectively): $W_t = P_t \nu_t \phi_t$. ν_t is an idiosyncratic transitory shock with $\log \nu_t \sim N\left(-\sigma_\nu^2/2, \sigma_\nu^2\right)$, while ϕ_t is a transitory displacement/disability ("bad") shock which reduces income by a proportion μ with a small probability p_ϕ. In turn, permanent income is $P_t = P_{t-1}\gamma_t \epsilon_t \varsigma_t$. Thus, permanent income growth, $\Delta \log P_t$, is the sum of a non-stochastic life-cycle component, $\log \gamma_t$, an idiosyncratic permanent shock, $\log \epsilon_t \sim N\left(-\sigma_\epsilon^2/2, \sigma_\epsilon^2\right)$, and an additional permanent "bad" shock $\log \varsigma_t$, which reduces permanent income by the proportion λ_t with a small probability p_ς. λ_t is allowed to vary with age, the cut being more drastic for older households.[19] Retirees receive a pension proportional to permanent earnings in the last period of their working life. That is, for a household born at time 0, $W_t = bP_R$, $\forall t > R$.[20]

Housing prices are uncertain and, following Li and Yao (2007), we assume that house-price appreciation is an i.i.d. normal process: $q_t/q_{t-1} - 1 = \varrho_t$, with $\varrho_t \sim N(\mu_\varrho, \sigma_\varrho^2)$. This specification implies that house-price shocks are permanent.[21] In our benchmark calibration, these shocks are serially uncorrelated and not correlated with household labor earnings.

4.2. Calibration

Our calibration is constructed to reproduce three statistics from the Survey of Consumer Finances: the homeownership rate, the median wealth-to-earnings ratio for working-age households, and the median ratio of home value to total wealth for homeowners (70 percent, 1.8, and .82, respectively).

To match the targets, we set the discount rate to 3.45 percent, the weight of housing in a Cobb-Douglas utility function to .2, and impose a minimum size of the house that consumers can purchase of 1.65 times permanent income. The general strategy in choosing the remaining parameters is to focus whenever possible on the empirical evidence for the median household (see Appendix F for details and Table 4 for parameter values).

[19] The combination of permanent and transitory bad shocks is meant to capture employment and/or disability shocks that may or may not affect income for more than one period and may affect households differently. We do not have disability and displacement separately in our regressions with simulated data, like in the regressions with PSID data, as we combine transitory and permanent displacement/disability shocks into one indicator for bad news.

[20] This simplification is required for computational reasons and is common in the literature. See, for example, Cocco, Gomes and Maenhout (2005).

[21] This assumption is common in the literature (e.g., Cocco 2005, Campbell and Cocco 2003), and greatly simplifies the computation of the model by facilitating a renormalization of the household problem with fewer state variables.

5. Simulations

We simulate 27 "regions" with 5,000 people each for a number of periods. House-price shocks are common to all individuals in a given region (there are only three possible house-price shocks), while all other shocks (income and moving shocks) are idiosyncratic. We set up the simulations so that in regions 1 through 9, the house-price shock is at the lowest value for the last four periods (house-price depreciation). In regions 10 through 18, the house-price shock is at the middle value (constant house prices), while in regions 19 through 27, the house-price shock is at the highest value (house-price appreciation). The results we present are calculated using the last five periods of the simulations (which represent 10 years, as one period in our model corresponds to two years).[22]

5.1. Regression results from simulated data

To match the specification in our empirical section, we use four-year log differences in consumption, income, and house prices, and overlapping growth rates in the regressions. Our bad news dummy equals 1 in period t if the household suffers a bad shock in periods t, $t-1$, $t-2$ or $t-3$ and not in $t-4$. As in the data, when presenting results by tenure status, we define a homeowner (renter) as a household that owned (rented) a house in all periods involved in calculating the consumption growth rate. To facilitate comparisons with our empirical results, we restrict our attention to households with heads aged 28–64. (As explained in Appendix C, households are born at age 24 and retire at age 66.)

Table 5, first panel, shows that 10 percent house-price appreciation results in a 2.7 percent increase in nondurable consumption for owners with no effect for renters. The direct effect of bad news is a drop in nondurable consumption of 17 percent for owners versus 21 percent for renters. The coefficients are estimated very precisely—the t-statistics

[22] Results are similar if we include more periods in our regressions, so we keep the sample smaller for tractability.

are much larger than those in the data which reflects that the model is a simplification where all consumers are a priori identical. Importantly, the sensitivity of consumption to income changes goes down when houses appreciate as shown by the estimated positive coefficient for the interaction term. Nondurable consumption drops by about a percent less if housing appreciates by 10 percent. Compared to the data, the coefficient to house prices is larger, maybe reflecting higher costs or more stringent financing constraints for some households in the real world. The effect of bad news is smaller in the real world while the interaction effect is smaller in the model—maybe reflecting informal help from family (who may live in the same MSA) or assets not present in the model.

The other panels in Table 5 explore the properties of the theoretical model in order to understand the impact of relative house prices, financing constraints, etc. on our results. The second panel shows the results for the case where there is no homeownership and "house prices" simply capture changes in rental prices. In this case, house price changes do not affect nondurable consumption directly or through the interaction with the bad-news shock. This set of results verifies that our findings regarding house prices are not due to changes in relative prices per se which, of course, reflects the specific utility function we use.[23]

The next set of results analyzes a model where homeownership can be obtained with no down payment. In this case, the barriers to home ownership are a minimum required size of the house and the potential trading costs if the house has to be sold again. These results are quite similar to the benchmark case, although the interaction effect is slightly larger, as a larger fraction of home equity can be used as collateral for loans. If, alternatively, there is a down payment but no transaction costs, the interaction term gets somewhat smaller

[23]The within-period preferences over consumption of nondurables and housing services are of Cobb-Douglas type. Thus, in the perfect rental market setting, consumers keep a fixed proportion of their spending on each type of good: if house prices go up, consumption of housing services goes down but nondurable consumption remains unchanged.

as homeowners can easily downsize making home equity completely liquid—talking about collateral in this case is purely semantics. The direct effect of bad news for renters is larger because they are less affluent in this simulation. Interestingly, there is a significant effect of house prices for renters. This effect can, for example, be due to older renters giving up on accumulating enough savings for a down payment and using part of their accumulated savings for nondurable consumption. The negative significant interaction effect could be due to young renters saving for a down payment, even after being hit by displacement shocks but we will not explore this issue further.

If there is no down payment, adjustment costs, or minimum house size requirement, house equity is fully liquid for all owners and the insurance effect measured by the interaction terms takes its largest value across the simulations. It appears that the liquidity of house equity is important for the direct effect of house prices: if housing consumption cannot be easily adjusted, nondurable consumption will react more strongly. The interaction effect is, however, larger when housing can be freely adjusted.

In the situation with a down payment of 100 percent, home equity is, in principle, not liquid and the interaction term becomes smaller. It is, however, still highly significant due to owners that have paid off their full mortgage. For such owners, an increase in house prices is associated with an increase in life-cycle savings as most owners will eventually sell the house and they are therefore willing to draw on their liquid (non-housing) wealth.

Finally, we allow for house-price growth to be perfectly correlated with income growth—in this case the direct effect of house prices is highly significant for renters also but the interaction effect is not. Because it is very hard to properly control for correlations between house prices and income, testing for insurance effects of house prices is more robust than testing for direct effects of house-price appreciation on consumption.

Table 6 summarizes the model's predictions when we split the sample by criteria similar to the splits used for the PSID data. The first panel shows that nondurable consumption reacts more strongly to house-price changes for non-movers. We continue with the young/old split. As in the empirical part, we classify households as young if their head is aged 45 or younger, and old if the head is over 50. We find that, as in the data, the effect of house-price appreciation on consumption (in the direction of more risk sharing) is strongest for old owners. Older owners have more equity and, likely more important, may be more willing to pay the adjustment cost because they plan to downsize to free up life-cycle savings anyway. The model results, however, do not display the very large difference found between the young and the old in the data. The significant interaction for old renters is likely due to some renters giving up on accumulating enough to ever obtain a house.

Considering the impact of wealth, we split the sample according to whether net worth is "liquid;" i.e., whether wealth is beyond 20 percent of the house value in the initial period. We see that the interaction term is larger for households with less liquid net worth—such households can access home equity by downsizing the residence (or moving to rental) but this group of consumers can only pay the transactions cost involved in moving by downsizing enough to make the 20 percent down payment which may explain the larger estimated interaction term.[24] I.e., housing wealth is effectively more "committed" for households with less liquid wealth which may be particularly important in the bad situation where bad news happen at a time of declining house prices. This result is consistent with the larger coefficients found for the SEO sample in the empirical section. The last panel reports results controlling for income growth. We find a significantly higher propensity to consume out of income for renters pointing towards less overall risk sharing for this group. Controlling for income also brings the coefficient to the direct effect of

[24] We verified that moving rates are much lower for households with low liquid wealth when displaced, particularly when houses depreciate. We do not tabulate moving frequencies due to space constraints.

bad news closer to its empirical counterpart, while having little effect on the interaction coefficients.

6. Conclusion

Using a calibrated theoretical model in which agents can own or rent, we show that homeowners are better able to share income risks than renters. Using household-level data from the PSID and house-price data from the FHFA, we find that U.S. households are significantly better able to maintain their level of consumption after job loss or disability if they are homeowners in MSAs where housing is appreciating. Our interpretation is that this results from most homeowners being able to access the capital gains either using equity as collateral or by selling the house.

The estimated coefficients are of economically significant magnitudes. For example, if we ignore the direct effect of house prices (which is likely to partly reflect left-out variables, such as expectations of future income), a homeowner who becomes disabled will see a drop in consumption of about 5 percent over a four-year period if house prices are constant but no change in consumption if house prices in the metro area increase by about 26 percent during the same time period. However, if house prices fall by, say, 40 percent—as is not uncommon in the wake of the 2008 subprime crisis—a staggering consumption drop of 12 percent can be expected for a homeowner who becomes disabled.[25]

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[25]This illustration is based on the coefficients in column (3) of Table 1 ignoring the direct effect of house-price appreciation.

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Table 1: Risk Sharing Regressions for Owners vs. Renters

	Owners			Renters			All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
House price G.	0.135***	0.136***	0.135***	0.222***	0.223***	0.213***	0.153***
	(5.68)	(5.82)	(5.92)	(4.88)	(4.90)	(4.86)	(8.17)
Disabled	–0.043***			–0.062***			
	(–4.06)			(–3.12)			
Disability × House price G.	0.329***			–0.174			
	(3.95)			(–1.32)			
Displaced		–0.043***			–0.076***		
		(–3.68)			(–4.30)		
Displaced × House price G.		0.155**			–0.082		
		(1.98)			(–0.62)		
Bad news			–0.047***			–0.070***	–0.060***
			(–4.66)			(–4.09)	(–7.48)
Bad news × House price G.			0.184***			0.012	0.118**
			(2.61)			(0.11)	(2.54)
Fam. size G.	0.335***	0.337***	0.334***	0.265***	0.273***	0.266***	0.307***
	(23.58)	(23.48)	(23.64)	(15.87)	(16.58)	(15.97)	(28.03)
Age	–0.009***	–0.009***	–0.009***	–0.005	–0.006	–0.005	–0.006**
	(–2.93)	(–2.88)	(–3.01)	(–0.87)	(–1.06)	(–0.94)	(–2.27)
Age sq./100	0.005	0.005	0.005	0.002	0.003	0.002	0.002
	(1.43)	(1.38)	(1.49)	(0.34)	(0.46)	(0.36)	(0.69)
Adj. R sq.	0.078	0.077	0.078	0.037	0.040	0.038	0.059
F	200.6	158.2	189.3	49.4	76.7	71.5	219.9
N	19,224	18,221	19,228	8,776	8,434	8,776	32,246

Notes: Sample is restricted to owners and renters defined as follows. Owners (renters) are households who continuously owned (rented) a house between years t and $t-4$, resided in the same MSA and did not change family composition during that time span. Serial correlation in the regression errors is corrected using the Prais-Winsten transformation; robust standard errors in the regressions clustered by the MSA where the household lives between years t and $t-4$. t-statistics in parentheses. *** (**) [*] significant at the 1 (5) [10]%.

Table 2: Risk sharing regressions—Data. Different samples

	Owners		Renters	
Main specification				
House Price G.	0.135***	(5.92)	0.213***	(4.86)
Bad news	–0.047***	(–4.66)	–0.070***	(–4.09)
Bad news × House price G.	0.184***	(2.61)	0.012	(0.11)
No of obs.		19,228		8,776
Non-movers/same residence				
House Price G.	0.132***	(5.73)	0.174**	(2.42)
Bad news	–0.042***	(–3.77)	–0.067***	(–3.05)
Bad news × House price G.	0.172**	(2.30)	0.098	(0.58)
No of obs.		16,573		4,343
Non-overlapping growth rates				
House Price G.	0.124***	(2.74)	0.212*	(1.85)
Bad news	–0.079***	(–4.95)	–0.083***	(–3.44)
Bad news × House price G.	0.356***	(3.03)	0.250	(1.51)
No of obs.		6,251		2,771
House-price residuals				
House Price G.	0.100***	(3.70)	0.180***	(3.92)
Bad news	–0.048***	(–4.79)	–0.070***	(–4.17)
Bad news × House price G.	0.180**	(2.20)	0.050	(0.41)
No of obs.		19,228		8,776
Young				
House Price G.	0.136***	(4.29)	0.246***	(4.01)
Bad news	–0.045***	(–3.01)	–0.055***	(–2.97)
Bad news × House price G.	0.044	(0.50)	–0.038	(–0.29)
No of obs.		8,835		5,581
Old				
House Price G.	0.122***	(4.09)	0.141	(1.64)
Bad news	–0.059***	(–4.63)	–0.113***	(–3.55)
Bad news × House price G.	0.304***	(3.05)	0.093	(0.43)
No of obs.		7,853		2,383
SEO sample				
House Price G.	0.205***	(4.61)	0.240***	(3.98)
Bad news	–0.039**	(–2.08)	–0.078***	(–3.24)
Bad news × House price G.	0.231*	(1.94)	–0.001	(–0.01)
No of obs.		6,191		5,663
Core sample				
House Price G.	0.104***	(4.34)	0.165***	(2.71)
Bad news	–0.049***	(–4.78)	–0.036*	(–1.67)
Bad news × House price G.	0.161*	(1.89)	0.013	(0.07)
No of obs.		13,037		3,113

Notes: We run the following regression: $c_{it} - \bar{c}_t = \mu + \beta\ (hp_{mt} - \overline{hp}_t) + \xi\ (D_{it} - \bar{D}_t) + \zeta\ (D_{it} - \bar{D}_t) \times (hp_{mt} - \overline{hp}_t) + (X_{it} - \bar{X}_t)'\delta + \varepsilon_{it}$. We control of age, age squared and family size growth in the regressions. Young is 25–45, old is 50–65. We report the estimated coefficients $\hat{\beta}$, $\hat{\xi}$ and $\hat{\zeta}$. Serial correlation in the regression errors is corrected using the Prais-Winsten transformation; robust standard errors in the regressions clustered by region. t-statistics in parentheses. *** (**) [*] significant at the 1 (5) [10]%.

Table 3: Risk sharing regressions—Data. Different samples. Robustness

	Owners		Renters	
Food at home				
House Price G.	0.145***	(5.93)	0.239***	(4.93)
Bad news	–0.033***	(–3.21)	–0.046***	(–2.85)
Bad news × House price G.	0.199***	(3.04)	0.022	(0.17)
No of obs.		19,228		8,776
Food away				
House Price G.	0.039	(0.79)	0.153	(1.62)
Bad news	–0.110***	(–5.64)	–0.116***	(–3.96)
Bad news × House price G.	–0.008	(–0.05)	0.038	(0.19)
No of obs.		16,488		5,951
1980–1994: limiting condition only				
House Price G.	0.131***	(4.67)	0.208***	(4.03)
Bad news	–0.032***	(–2.64)	–0.064**	(–2.51)
Bad news × House price G.	0.317***	(3.46)	–0.220	(–1.42)
No of obs.		10,504		5,813
1994–2005: limiting condition only				
House Price G.	0.132***	(3.44)	0.276***	(4.10)
Bad news	–0.054***	(–2.99)	–0.060**	(–2.14)
Bad news × House price G.	0.328**	(2.22)	0.017	(0.08)
No of obs.		10,023		3,478
Imputed nondurables				
House Price G.	0.144***	(4.48)	0.251***	(4.07)
Bad news	–0.050***	(–3.75)	–0.062**	(–2.42)
Bad news × House price G.	0.174*	(1.74)	0.098	(0.62)
No of obs.		14,274		6,168
Controlling for income				
Income G.	0.107***	(11.50)	0.186***	(12.71)
House Price G.	0.118***	(5.53)	0.152***	(3.42)
Bad news	–0.037***	(–3.60)	–0.051***	(–2.93)
Bad news × House price G.	0.171**	(2.58)	0.053	(0.47)
No of obs.		18,431		8,220

Notes: See notes to Table 2.

Table 4: Benchmark Calibration Parameters

Preferences	
	Cobb-Douglas utility; .205 weight for housing.
	Discount rate 3.45%; curvature of utility 2.
Demographics	
	One period is two years.
	Households are born at 24, retire at 66 and die at 84 the latest.
	Mortality shocks: U.S. vital statistics (females), 2003.
Income	
	Overall variance of permanent (transitory) shocks .01 (.073).
	Displacement: Perm. shock: probability 3%; income loss 25 (40)% for young (old).
	Transitory shock: probability 5%; income loss 40%.
	Jointly match s.d. of "bad news" in the PSID.
	Pension: 50% of last working period permanent income.
Interest rates	
	4% for deposits; 4.5% for mortgages.
	No uncertainty.
Housing Market	
	Down payment 20%; buying (selling) cost 2% (6%).
Taxes	
	Proportional taxation.
	Income tax rate 20% (TAXSIM); mortgage interest fully deductible.
House Prices	
	Average real appreciation 0; variance .0131;
	Housing depreciation 1.5%
	Rent-to-price ratio 5.7%
	Moving defined as increasing or decreasing housing services more than 5%.
Moving shocks	
	1.5% probability when working-age; to match moving rates in PSID.
Other	
	No income and house-price correlation.
	No bequest motive but accidental bequests.

Table 5: Risk sharing regressions–Model. Alternative Calibrations

	Owner		Renter	
Baseline (70% ownership)				
House Price G.	0.27***	(140.39)	0.01	(1.56)
Bad news	–0.17***	(–120.89)	–0.21***	(–69.05)
Bad news × House price G.	0.08***	(16.69)	–0.01	(–0.91)
No. of obs.		151,150		62,126
Ownership not allowed (0% ownership)				
House Price G.			0.00	(1.61)
Bad news			–0.17***	(–131.54)
Bad news × House price G.			0.00	(0.39)
No. of obs.				254,593
No downpayment (72% ownership)				
House Price G.	0.28***	(121.47)	0.01**	(2.41)
Bad news	–0.17***	(–150.06)	–0.21***	(–76.75)
Bad news × House price G.	0.09***	(19.87)	–0.02	(–1.55)
No. of obs.		146,289		66,021
No adj. cost (90% ownership)				
House Price G.	0.25***	(162.12)	0.03**	(2.54)
Bad news	–0.16***	(–125.98)	–0.34***	(–32.91)
Bad news × House price G.	0.06***	(14.56)	–0.10***	(–3.17)
No. of obs.		221,600		7,154
No dowpayment, adj. cost or min. house size (100% ownership)				
House Price G.	0.23***	(147.41)		
Bad news	–0.17***	(–81.62)		
Bad news × House price G.	0.11***	(16.98)		
No. of obs.	254,593			
100% downpayment (60% ownership) ♯				
House Price G.	0.16***	(60.14)	–0.00	(–0.02)
Bad news	–0.19***	(–115.31)	–0.23***	(–99.23)
Bad news × House price G.	0.05***	(7.91)	0.01	(0.89)
No. of obs.		142,000		82,819
Income/house price correlation (70% ownership)‡				
House Price G.	0.39***	(219.91)	0.20***	(51.93)
Bad news	–0.17***	(–131.59)	–0.21***	(–80.83)
Bad news × House price G.	0.06***	(14.24)	–0.01	(–1.17)
No. of obs.		156,217		62,983

Notes: We run the following regression: $c_{it} - \bar{c}_t = \mu + \beta\,(hp_{mt} - \overline{hp}_t) + \xi\,(D_{it} - \bar{D}_t) + \zeta\,(D_{it} - \bar{D}_t) \times (hp_{mt} - \overline{hp}_t) + (X_{it} - \bar{X}_t)'\delta + \varepsilon_{it}$. We report the estimated coefficients $\hat{\beta}$, $\hat{\xi}$ an $\hat{\zeta}$. We control for age and age squared in the regressions. ♯ house size restriction eliminated to increase homeownership. ‡ recalibrated to match the same targets as in the benchmark. Serial correlation in the regression errors is corrected using the Prais-Winsten transformation; robust standard errors in the regressions clustered by region. t-statistics in parentheses. *** (**) [*] significant at the 1 (5) [10]%.

Table 6: Risk sharing regressions–Model. Different Splits

	Owner		Renter	
<u>Baseline</u>				
House Price G.	0.27***	(140.39)	0.01	(1.56)
Bad news	–0.17***	(–120.89)	–0.21***	(–69.05)
Bad news × House price G.	0.08***	(16.69)	–0.01	(–0.91)
No. of obs.		151,150		62,126
<u>Non-movers</u>				
House Price G.	0.34***	(52.56)	0.01	(1.56)
Bad news	–0.15***	(–97.43)	–0.21***	(–69.05)
Bad news × House price G.	0.10***	(18.14)	–0.01	(–0.91)
No. of obs.		121,970		62,126
<u>Young</u>				
House Price G.	0.25***	(65.79)	0.00	(1.13)
Bad news	–0.14***	(–49.70)	–0.25***	(–69.18)
Bad news × House price G.	0.05***	(6.08)	–0.01	(–0.98)
No. of obs.		30,451		40,425
<u>Old</u>				
House Price G.	0.29***	(152.53)	0.03**	(2.59)
Bad news	–0.19***	(–84.34)	–0.11***	(–28.37)
Bad news × House price G.	0.11***	(13.69)	0.04***	(3.11)
No. of obs.		73,829		5,897
<u>Poor</u>				
House Price G.	0.36***	(41.82)	0.01	(1.16)
Bad news	–0.19***	(–44.05)	–0.18***	(–50.81)
Bad news × House price G.	0.15***	(9.83)	–0.00	(–0.25)
No. of obs.		9,607		34,888
<u>Rich</u>				
House Price G.	0.23***	(112.77)	0.04	(1.03)
Bad news	–0.15***	(–51.58)	–0.10***	(–4.33)
Bad news × House price G.	0.06***	(5.51)	–0.01	(–0.19)
No. of obs.		49,231		435
<u>Controlling for current income</u>				
Income G.	0.12***	(158.59)	0.30***	(186.42)
House Price G.	0.27***	(180.72)	0.01	(1.60)
Bad news	–0.10***	(–82.99)	–0.08***	(–36.33)
Bad news × House price G.	0.07***	(17.32)	–0.02**	(–2.10)
No. of obs.		151,150		62,126

Notes: We run the following regression: $c_{it} - \bar{c}_t = \mu + \beta\,(hp_{mt} - \overline{hp}_t) + \xi\,(D_{it} - \bar{D}_t) + \zeta\,(D_{it} - \bar{D}_t) \times (hp_{mt} - \overline{hp}_t) + (X_{it} - \bar{X}_t)'\delta + \varepsilon_{it}$. We report the estimated coefficients $\hat{\beta}$, $\hat{\xi}$ and $\hat{\zeta}$. We control for age and age sq. in the regressions. Young is 28–45, old is 50–64. Poor (Rich) if below (above) the 25 (75)-th percentile of net worth–(0.2 × house value) in the initial period. Serial correlation in the regression errors is corrected using the Prais-Winsten transformation; robust standard errors in the regressions clustered by region. t-statistics in parentheses. *** (**) [*] significant at the 1 (5) [10]%.

Appendices

Appendix A Risk Sharing with housing. Derivation of equation (1)

Consider an endowment economy with nondurable and housing goods, C and H respectively. Each time a stochastic event s_t is drawn from the state space S. The probability of drawing a sequence of states $s^t = (s_1, \ldots, s_t)$ is denoted as $\pi(s^t)$. Individual endowments of housing services and nondurable consumption goods at time t depend on s^t.

Consider the Pareto problem where a social planner maximizes the discounted utility flows of N agents in the economy:

$$\max \sum_{i=1}^{N} \omega_i \sum_{t=1}^{\infty} \sum_{s^t} \beta^t \pi(s^t) u\left[C_i(s^t), H_i(s^t), \delta_i(s^t)\right] \tag{A-1}$$

s.t. the feasibility constraints:

$$\sum_{i=1}^{N} C_i(s^t) \leq C(s^t) \text{ for all } t, s^t \tag{A-2}$$

$$\sum_{i=1}^{N} H_i(s^t) \leq H(s^t) \text{ for all } t, s^t, \tag{A-3}$$

where ω_i is the planner's weight attached to individual i's welfare and the weights sum to one; β is the time discount factor; $C(s^t)$ is the aggregate endowment of nondurable consumption goods at time t, history of events s^t; $H(s^t)$ is the aggregate endowment of housing services at time t, history s^t; and $\delta_i(s^t)$ is consumer i's shock to tastes over consumption of nondurables and housing services at time t history of events s^t. Let the instantaneous utility function be $u(C, H) = \frac{\delta_i (C^{\alpha} H^{1-\alpha})^{1-\sigma}}{1-\sigma}$. Denote the Lagrange multipliers attached to the nondurables feasibility constraint as $\theta(s^t)$ and the housing feasibility constraint as $\lambda(s^t)$. The maximization problem with respect to $C_i(s^t)$ and $H_i(s^t)$ yields the following first-order conditions:

$$\omega_i \beta^t \delta_i(s^t) \alpha \frac{\left[C_i(s^t)^{\alpha} H_i(s^t)^{1-\alpha}\right]^{1-\sigma}}{C_i(s^t)} = \frac{\theta(s^t)}{\pi(s^t)} \equiv \theta'(s^t), \tag{A-4}$$

$$\omega_i \beta^t \delta_i(s^t)(1-\alpha) \frac{\left[C_i(s^t)^{\alpha} H_i(s^t)^{1-\alpha}\right]^{1-\sigma}}{H_i(s^t)} = \frac{\lambda(s^t)}{\pi(s^t)} \equiv \lambda'(s^t). \tag{A-5}$$

Denoting a generic random variable $x(s^t)$ as x_t, it can be shown that the two equations imply the following relationship for individual i's growth of nondurable consumption:

$$\Delta \log C_{it} = \frac{1}{1+\gamma+\phi} \left[-\phi \Delta \log \theta'_t + (1+\phi) \Delta \log \lambda'_t - \Delta \log \delta_{it} - \log \beta\right] + \epsilon_{it}, \tag{A-6}$$

where $\gamma \equiv \alpha(1-\sigma)-1$, $\phi \equiv (1-\alpha)(1-\sigma)-1$, and ϵ_{it} is individual i's measurement error in nondurable consumption growth.

In our empirical analysis, we consider four-year differences defined as $c_{it} \equiv \log C_{it} - \log C_{it-4} = \sum_{j=0}^{3} \Delta \log C_{it-j}$. Equation (A-6) can be rewritten as:

$$c_{it} = \frac{1}{1+\gamma+\phi}\left[-\phi\tilde{\theta}_t + (1+\phi)\tilde{\lambda}_t - \tilde{\delta}_{it} - \tilde{\beta}\right] + \tilde{\epsilon}_{it}, \tag{A-7}$$

where $\tilde{\theta}_t = \sum_{j=0}^{3} \Delta \log \theta'_{t-j}$; $\tilde{\lambda}_t = \sum_{j=0}^{3} \Delta \log \lambda'_{t-j}$; $\tilde{\delta}_{it} = \sum_{j=0}^{3} \Delta \log \delta_{it-j}$; $\tilde{\beta} = 4\log\beta$; and $\tilde{\epsilon}_{it} = \sum_{j=0}^{3} \epsilon_{it-j}$.

Subtracting nationwide consumption growth, $\bar{c}_t$, from idiosyncratic consumption growth, we obtain:

$$c_{it} - \bar{c}_t = u_{it}, \tag{A-8}$$

where $u_{it} = \tilde{\epsilon}_{it} + \frac{1}{1+\gamma+\phi}\left(\tilde{\bar{\delta}}_t - \tilde{\delta}_{it}\right)$, $\bar{c}_t$ and $\tilde{\bar{\delta}}_t$ are the nationwide averages of nondurable consumption growth and taste shocks.

Equation (A-8) says that any idiosyncratic variable, D_{it} net of the nationwide average (and its interaction with any aggregate variable, say, regional house-price growth) independent of taste shocks and measurement error in nondurable consumption growth should not enter significantly in a regression of the form:

$$\begin{aligned} c_{it} - \bar{c}_t = &\mu + \beta\left(hp_{mt} - \overline{hp}_t\right) + \xi\left(D_{it} - \bar{D}_t\right) \\ &+ \zeta\left(D_{it} - \bar{D}_t\right) \times \left(hp_{mt} - \overline{hp}_t\right) + (X_{it} - \bar{X}_t)'\delta + \varepsilon_{it}, \end{aligned} \tag{A-9}$$

where hp_{mt} denotes house-price growth in the region of household i's residence m. The full risk-sharing allocation of housing services and nondurable consumption therefore implies testing the null that coefficients β, ξ and ζ are all equal to zero.

If nondurable consumption can be fully shared nationally across N agents but housing services can be freely transferred only within regions, the feasibility constraint for housing services will take the following form:

$$\sum_{i=1}^{N_m} H_{im}(s^t) \leq H_m(s^t) \text{ for all } t, s^t, \tag{A-10}$$

where N_m is the number of households residing in region m. $H_m(s^t)$ is the aggregate stock of housing services in region m at time t history of events s^t, and $H_{im}(s^t)$ is individual i's endowment of housing services at time t history s^t residing in region m. Denote the Lagrange multiplier attached to the housing feasibility constraint in region m at time t history of events s^t as $\lambda_m(s^t)$. In this case, equation (A-6) becomes:

$$\Delta \log C_{it} = \frac{1}{1+\gamma+\phi}\left[-\phi \Delta \log \theta_t' + (1+\phi)\Delta \log \lambda_{mt}' - \Delta \log \delta_{it} - \log \beta\right] + \epsilon_{it}. \tag{A-11}$$

Subtracting the nationwide average of nondurable consumption growth over the four-year interval from idiosyncratic consumption growth, we obtain:

$$c_{it} - \overline{c}_t = \frac{1+\phi}{1+\gamma+\phi}\left(\tilde{\lambda}_{mt} - \tilde{\lambda}_t\right) + u_{it}, \tag{A-12}$$

where $u_{it} = \epsilon_{it} + \frac{1}{1+\gamma+\phi}\left(\tilde{\delta}_t - \tilde{\delta}_{it}\right)$, and $\tilde{\lambda}_{mt} = \sum_{j=0}^{3} \Delta \log \lambda_{mt-j}'$ and $\tilde{\lambda}_t$ is the nationwide average of $\tilde{\lambda}_{mt}$. In this situation, consumption growth is higher if the housing constraint in the region of agent i tightens—implying an increasing value of the Lagrange multiplier.

In a decentralized competitive equilibrium with Arrow-Debreu securities for non-durable consumption and housing services, λ_{mt}' will be related to the regional price of housing services in terms of nondurable consumption goods.[26] Equation (A-12) suggests that any idiosyncratic variable D_{it} net of the nationwide average (as well as its interaction with the regional house-price growth net of aggregate house-price growth) independent of taste shocks and measurement error in nondurable consumption growth should not enter significantly the regression (A-9). Under the null of full risk sharing of housing services and nondurable consumption β, ξ and ζ are all equal to zero, while under the null of full risk sharing of nondurable consumption but regional risk sharing of housing services ξ and ζ are equal to zero while β is not equal to zero.

Appendix B Data

The PSID started in 1968 with a representative sample of about 3,000 households (the core sample) and a sample of low-income households (the SEO sample) that comprised about 2,000 families. In 1990 the PSID added the Latino sample and in 1997—the Immigrant sample. The PSID follows families over time, including young adults as they split off from the original family units. We use the core and SEO samples in our analysis, dropping the Latino and Immigrant samples. In 1997, the PSID changed from interviewing annually to interviewing biennially.

Our sample selection is as follows. We start with the individual file that contains information on age, sex, education, employment and headship status, and individual year of birth for years 1968–2007. We drop those who are never heads of household during

[26] It can be shown that a decentralized competitive equilibrium with time-0 Arrow-Debreu claims to nondurable consumption and housing services is a particular Pareto optimal allocation with $q^0(s^t) = \theta(s^t)$, and $hp_m^0(s^t) = \lambda_m(s^t)$ where $q^0(s^t)$ is the time 0 Arrow-Debreu price of one unit of nondurable consumption in terms of time 0 nondurable goods to be delivered if state s^t is realized at time t, and $hp_m(s^t)$ is the time 0 price of one unit of housing services in terms of time 0 nondurable goods to be delivered if state s^t is realized at time t.

the survey years. Individual age is reported with noise in the PSID: first, interviews may be conducted in different months of a year and, as a result, age may change or jump by more than one year in consecutive surveys; second, age can be recorded with error by interviewers. We utilize the data on year of birth from the individual file to construct a cleaner measure of age: age is defined as the difference between the survey year and year of birth. For those heads with no information on year of birth, we utilize the first record on age when an individual becomes a head to construct a consistent age series.

We further add the data on marital status, family composition change, family size, head's and wife's labor and transfer income, displacement and disability status, homeownership status, moving, self-reported house value and food from the family files of the PSID. We keep households whose heads are of ages 25 to 65, drop those with no information on food at home, homeownership status, and region of residence during the survey years. In the PSID, a small number of households report being neither owners nor renters in any survey year. We label those households owners if they report a positive house value; otherwise, we label them renters. Our results are robust to dropping those households. We set the homeownership status to missing if households report being owners and zero house value at the same time. We also set top-coded observations on income, house value, food at home, food away, and family size to missing.

Food consumption consists of food consumed at home and away from home (excluding food purchased at work or school). The PSID reported annual food costs until 1993, but has reported costs at the daily, weekly, biweekly, monthly, or annual frequency since 1994. For the years 1994–2005, we use household food consumption reported at the monthly or weekly frequency and convert those records to annual amounts.[27] For household income we use the sum of real labor and transfer income of head and wife before taxes. We deflate food consumption at home and away from home and household income by the all-items-less-housing consumer price index (CPI) from the Bureau of Labor Statistics.

In the PSID the timing of several variables is not fully synchronized. For example, the income record in a survey year t refers to the income earned in period $t-1$—the same holds for displacement status. Since most households are interviewed in the first quarter of the year, we assume that food consumption and limiting status records in a survey year t refer to the food consumption and limiting status effective in period $t-1$. Similarly, demographic variables such as age and family size are assumed to correspond to the head's age and family size in period $t-1$.[28] The house-price index in year t is the house-price index for the previous year.

Our further sample selection criteria are as follows. For each year, we keep observations with non-zero and non-missing records of food consumption at home. To hedge against outliers, we drop observations above the 99th percentile and below the 1st percentile of the annual food-at-home distributions. We further set to missing the records of food away from home above the 99th percentile of each annual distribution.[29] We then add up real

[27]We lose a low number of observations for households reporting food consumption at other frequencies. We do not include them in our sample because some, when converted to annual amounts, are clear outliers.

[28]This is necessary to enable us to keep observations after 1997, when the PSID switched to biennial data collection.

[29]We do not drop observations with zero records of food away from home. In the Consumer Expendi-

food at home and food away from home to obtain a measure of total food consumption. We drop observations with a ratio of total food consumption to income above the 99th percentile or below the 1st percentile of the annual distributions for the ratio. We also drop observations above the 99th percentile and below the 1st percentile of the four-year consumption growth distributions. We restrict our analysis to family-year pairs with stable composition (same head and wife during the four-year span) and families for which we have information on housing status. We also restrict our sample to households that reside in the same metropolitan area during a given four-year period so we can meaningfully assign to them four-year MSA house-price changes.

Appendix C House-price appreciation across MSAs

Figure A-1 shows the distribution of real house-price appreciation (four-year growth rates to match our empirical specification) over the period. As is evident from the distribution, our sample includes both house-price appreciation and house-price depreciation episodes. Figure A-2, panel (a) reveals significant cross-sectional variation of house-prices while panel (b) shows a clear difference in the intertemporal patterns of house-price appreciation for selected MSAs. Overall, this figure demonstrates the large variation in the panel of house prices which allows us to obtain statistically significant estimates of their impact on nondurable consumption.

Appendix D Total (imputed) nondurable consumption

Much of the theoretical and empirical research in this area focuses on the response of total nondurable consumption to income changes. Although the PSID does not collect measures of total nondurable consumption, Blundell et al. (2008) impute nondurable consumption of PSID households in a study of the joint dynamics of consumption and income inequality in the United States. Using data from the Bureau of Labor Statistics' Consumer Expenditure Survey (CEX) for 1980–1992, these authors estimate a structural equation for food consumption as a function of nondurable consumption and demographics, and invert the estimated equation to obtain a measure of nondurable consumption for PSID households. We follow their imputation strategy here. We use extracts of the CEX for 1980–2002 from the NBER.

In the CEX, households report at most four quarterly observations on consumption components. We use data for households that respond in all four quarters. The first report of consumption may be in different quarters and months of a quarter. If household consumption is recorded in both years t and $t+1$, we assume that annual consumption refers to year t if that year contains at least six months of consumption records, and to year $t+1$ otherwise. In the PSID, heads are males in households with couples, while in the CEX heads are considered to be those who rent or own the unit of residence. To make the definitions of heads compatible, we assume that heads are males in the

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tures Survey, which provides reliable information on the spending patterns of U.S. consumers, virtually everyone reports non-zero records of food at home, while a substantial fraction of respondents reports zero expenditures on food away from home (excluding food at work).

CEX families with couples. We drop households whose heads are part-time or full-time college students. As in our selection rules for the PSID sample, we drop observations for households with zero or missing records for food consumption at home. We further trim the annual distribution of total food below the 1st and above the 99th percentiles. Our final CEX sample contains households whose heads are 25–65 years old and born between 1915 and 1978. Our measure of nondurable consumption is the sum of annual expenditures on food at home, food away from home, food at work, alcohol and tobacco, clothes and personal care, domestic services, transportation (such as gasoline, tolls, and insurance), airfares, entertainment, gambling and charity, and utility payments.

In Table A-3, we report the results of an IV regression of food consumption on our measure of nondurable consumption, demographic controls, and prices.[30] The expenditure elasticity of food consumption is high in the 1980s, and drops steadily to about 0.73 in 2002.

We use the estimated coefficients in Table A-3 to impute nondurable (non-housing) consumption to PSID households for 1980–2002. This time span is shorter than that used in our previous food regressions, and as a result our samples are smaller. Table A-4 repeats our baseline regressions for this measure of (imputed) nondurable consumption. The results from this specification are very similar to those of the baseline regression using food expenditure.

Appendix E Results using home equity

Table A-5 explores if the *level* of accumulated housing equity helps homeowners smooth persistent shocks to their incomes. Housing equity is calculated as the difference between self-reported house value and the value of all mortgages on the house. Cross-sectional differences in housing equity do not appear to explain the ability of homeowners to insure against the shocks of displacement or disability as revealed in an insignificant and small interaction of lagged housing equity and bad news in column (1). In column (2), we explore the effect of shocks to (lagged) housing equity, measured by house-price growth at the MSA level, controlling for cross-sectional differences in lagged housing equity. The results are consistent with our previous analysis: households' ability to smooth persistent shocks improves if there is a shock to the collateral value of the house. We also estimated IV regressions of consumption growth on the observed changes in housing equity and changes in housing equity interacted with bad news, using house-price growth at the MSA level and house price growth interacted with bad news as instruments. Those regressions, not reported for brevity, delivered results similar to the baseline results for owners.

[30] In an OLS setting, the estimated elasticities may be biased because of measurement error in nondurable consumption, and because of endogeneity of food and nondurable consumption. We therefore follow Blundell et al. (2008), and instrument log nondurable consumption (and its interactions with year and education dummies) with the head's sex-education-year-cohort specific averages of log hourly wages (and their interactions with year and education dummies).

Appendix F The Household Problem and Calibration

The household problem

The problem solved by a newborn at time 0 can be written as:

$$\max_{\{C_t, F_t, H_t, A_t, M_t, x_t\}_{t=0}^{T}} E_0 \sum_{t=0}^{T} \frac{1}{(1+\rho)^t} \zeta_t U \left(C_t, \underbrace{(1-x_t) F_t + x_t H_t}_{=J_t} \right), \tag{A-13}$$

subject to

$$C_t \geq 0,\, F_t \geq 0,\, H_t \geq 0,\, A_t \geq 0,\, M_t \geq 0,\, x_t \in \{0,1\},\, z_t \in \{0,1\},\, \forall t = 0, \ldots, T, \tag{A-14}$$

$$\begin{aligned} &C_t + (1-x_t)\, r^f F_t + A_t - M_t + x_t (1 + I\,\kappa)\, q_t H_t + x_{t-1} I\, \chi q_t (1-\delta_h) H_{t-1} + \tau_y Y_t^{\tau} \leq \\ &\quad W_t + (1+r^a)\, A_{t-1} - (1+r^m)\, M_{t-1} + x_{t-1} q_t (1-\delta_h) H_{t-1},\ \forall t = 0, \ldots, T, \end{aligned} \tag{A-15}$$

$$\begin{aligned} &W_t = P_t \nu_t \phi_t, \quad P_t = P_{t-1} \gamma_t \epsilon_t \varsigma_t, \quad \forall t \leq R. \quad W_t = b P_R,\ \forall t > R, \\ &\varsigma_t = \begin{cases} \lambda_t < 1, & p_{\varsigma}, \\ 1 & 1 - p_{\varsigma}. \end{cases} \text{ and } \phi_t = \begin{cases} \mu < 1, & p_{\phi}, \\ 1 & 1 - p_{\phi}, \end{cases} \end{aligned} \tag{A-16}$$

$$Y_t^{\tau} = W_t + r^a A_{t-1} - \tau_m r^m M_{t-1},\ \forall t = 0, \ldots, T, \tag{A-17}$$

$$\begin{aligned} &M_t \leq (1-\theta)\, q_t H_t \text{ or} \\ &M_t < M_{t-1} \text{ if } M_t > (1-\theta)\, q_t H_t \text{ and } (|H_t/H_{t-1} - 1| < 0.05, z_t = 0), \\ &\qquad \forall t = 0, \ldots, T-1;\ M_T = 0, \end{aligned} \tag{A-18}$$

$$q_{t+1} = (1 + \varrho_{t+1})\, q_t,\ \forall t = 0, \ldots, T. \tag{A-19}$$

Equation (A-14) contains non-negativity constraints, and states that households cannot be renters and homeowners at the same time (x_t is an indicator of ownership in period t and F_t are housing services acquired through the rental market), and face moving shocks. Equation (A-15) is the budget constraint, where I is an indicator function equal to 1 if the household is moving and 0 otherwise. Equation (A-16) describes labor income for working-age households, and the pension benefit for retirees. Equation (A-17) spells out taxable income. Equation (A-18) is the collateralized debt constraint, which says that the maximum loan-to-value ratio for new mortgages and equity lines of credit is $1-\theta$, allowing for an exception for non-movers (when prices go down) who can simply pay their mortgage. Finally, equation (A-19) captures the dynamics of housing prices.

Under these assumptions, households prefer equity to debt financing of their houses (i.e., they pay their mortgages before accumulating deposits), as long as the after-tax rate on mortgages, $(1-\tau_m \tau_y) r^m$, is higher than the after-tax return on deposits, $(1-\tau_y) r^a$.

For details on the solution method, see Díaz and Luengo-Prado (2010).

Calibration Details

Preferences, endowments and demography

For computational reasons, one period is two years. Households are born at age 24 ($t = 1$), and die at the maximum age of 85 ($t = 31$). The retirement age is 66 ($t = 22$). Survival probabilities are taken from the latest U.S. Vital Statistics (for females in 2003), published by the National Center for Health Statistics. The implied fraction of working-age households is 75.6 percent—slightly lower than the fraction in the PSID, 78.6 percent. Most parameters are quoted in annual terms, but are adjusted to a biennial frequency in our computations.

For preferences regarding consumption of nondurable goods and housing services, we choose the non-separable Cobb-Douglas utility function:

$$U(C, J) = \frac{(C^{\alpha} J^{1-\alpha})^{1-\sigma}}{1-\sigma}. \tag{A-20}$$

The curvature of the utility function is $\sigma = 2$.

We follow Cocco et al. (2005) in our labor earnings calibration. Using data from the PSID, those authors estimate the life-cycle profile of income, as well as the variance of permanent and transitory shocks for three different educational groups: no high school, high school, and college. We choose these authors' estimates of the variance of permanent and transitory shocks for households whose head has a high school degree—the typical median household (0.01, and 0.073, respectively). These values are typical in the literature—Storesletten, Telmer and Yaron (2004). For consistency, we also use the estimated growth rate of the non-stochastic life-cycle component of earnings for a household with a high school degree from Cocco et al. (2005).

To calibrate the displacement shock, we follow the evidence in Stephens (2001). The literature on job displacement finds that annual earnings fall 25–40 percent in the year of displacement, while earnings fall by roughly 15 percent after a disability shock. Annual earnings are well below expected levels six years after the initial shock in both cases. We model displacement as a combination of permanent and transitory shocks. We set the income loss from the permanent shock to the lower end of his findings for the young, 25 percent, and to the upper end, 40 percent, for the old (young is under 46, old is 46-64 so λ_{young}=0.75 and λ_{old}=0.60). The probability of the permanent displacement shock is 3 percent, a bit below the 5–15 percent found using datasets such as the PSID. (Numbers vary depending on the specific definitions of displacement and disability.) Cocco et al. (2005) do not allow for a displacement shock, so σ_ε^2 is adjusted so that the overall variance of the permanent shocks inclusive of this bad shock is equal to their estimate, .01. The transitory displacement shock is calibrated to produce a loss of income of 40 percent for just one period with a 5 percent probability. As with the permanent shocks, σ_ν^2 is adjusted so that the overall variance of the transitory shocks is .073 as in Cocco et al. (2005). This combination of permanent and transitory bad shocks reproduces the mean and standard deviation of the bad news variable constructed from PSID data and used in our regressions. In our model, retirees face no income uncertainty. Their pension is set at 50 percent of permanent income in the last period of working life. That figure is between the 42 percent estimated in Munnell and Soto (2005) as the median replacement rate for newly retired workers, according to both the Health Retirement Survey and Social Security Administration data, and the 68 percent in Cocco et al. (2005), calculated as a ratio of average income for retirees and average income in the last working year before retirement (PSID data). The moving shock is calibrated to match the four-year moving rate for owners in PSID data which is 19 percent. We need an annual moving probability of 1.5 percent to get this rate in our model. Only working-age individuals are affected by the moving shock.

In our setup, there is no age limit on credit availability and, in the event of death, houses are liquidated at the price in the previous period to avoid most negative accidental bequests. A negative bequest is still possible for a homeowner who dies at a young age after a period of house-price depreciation. We assume the government takes the loss in this case.

Market arrangements

The minimum down payment is 20 percent, slightly below the 25 percent average down payment for the period 1963–2001 reported by the Federal Housing Finance Board. We set the selling cost equal to 6 percent, a typical realtor fee, and the buying cost to 2 percent. The interest rate on deposits, r^a, is set to 4 percent in annual terms (the average real rate for 1967–2005, as calculated in Díaz and Luengo-Prado 2010), while the interest rate on mortgages is set to 4.5 percent.

Taxes

To calibrate the income tax rate, τ_y, we use data on personal income and personal taxes from the National Income and Product Accounts of the Bureau of Economic Analysis, as well as information from TAXSIM, the NBER tax calculator.[31] For the period 1989–2004, personal taxes represent 12.47 percent of personal income in NIPA. As in Prescott (2004), we multiply this number by 1.6 to reflect the fact that marginal income tax rates are usually higher than average rates. The 1.6 number is the mean ratio of marginal income tax rates to average tax rates, based on TAXSIM (for details, see Feenberg and Coutts 1993). The final number is 19.96 percent, which we approximate using $\tau_y = .20$. We assume mortgage payments are fully deductible, $\tau_m = 1$.

House prices

Housing prices follow the process $q_t = q_{t-1}(1 + \varrho_t)$, where $\varrho_t \sim N(\mu_\varrho, \sigma_\varrho^2)$. $\mu_\varrho = 0$ and $\sigma_\varrho^2 = .0132$—as in Li and Yao (2007). We assume ϱ_t is serially uncorrelated and uncorrelated with the income shocks. The housing depreciation/maintenance cost rate, δ^h, is set to 1.5 percent, as estimated in Harding, Rosenthal and Sirmans (2007).

[31] The TAXSIM data is available at `http://www.nber.org/taxsim`.

The rental price is proportional to house prices. In particular:

$$r_t^f = \frac{q_t - E_t\left[\frac{1}{1+(1-\tau_y)r^a}\, q_{t+1}\left(1-\delta^h\right)\right]}{1-\tau_y} = q_t\ \frac{(1-\tau_y)r^a + \delta_h}{(1-\tau_y)(1+(1-\tau_y)r^a)}, \tag{A-21}$$

which can be interpreted as the user cost for a landlord who is not liquidity constrained, not subject to adjustment costs, and who pays income taxes on rental income. This calibration choice is consistent with the estimates in Sinai and Souleles (2005), who find the house-price-to-rent ratio capitalizes expected future rents, as any other asset (for more details see Díaz and Luengo-Prado 2010). For our benchmark calibration, r_t^f/q_t is roughly 5.7 percent annually.

Patterns of homeownership and wealth

Figure A-3 depicts the evolution of some key variables throughout the life cycle in our baseline calibration. All series are normalized by mean earnings. Panel *(a)* shows mean labor income (earnings for workers and pensions for retirees) and nondurable consumption. For working-age households, the life-cycle profile for earnings is calibrated to the profile estimated by Cocco et al. (2005) for households with a high school degree. Earnings peak at age 47. For retirees, the pension-replacement ratio is calibrated to be 50 percent of permanent earnings in the last working period. Our model produces a hump-shaped nondurable consumption profile with a peak around age 60.

Panel *(b)* in Figure A-3 depicts mean wealth and its different components throughout the life cycle. Total wealth is hump-shaped and peaks at ages 60–63, with a value about 2.96 times mean earnings in the economy, declining rapidly afterward. Because we do not allow for altruism in the model, total wealth is zero for those who reach the oldest-possible age (not depicted). Housing wealth (including collateralized debt) increases until age 52–55, then stays fairly constant until it begins to decrease at age 72, when the homeownership rate starts to decline. Financial assets become negative at age 72 as retirees take advantage of reverse mortgages.

The targets of our calibration are the overall homeownership rate in the United States, the median wealth-to-earnings ratio for working-age households, and the median ratio of house value to total wealth for homeowners. Figure A-4 plots the life-cycle patterns of these three variables against the data.[32] The median wealth-to-earnings ratio in the model—see panel *(a)*—follows the ratio in the data very closely until age 59, and diverges significantly thereafter, probably because we are not allowing for heterogeneity in retirement ages. In our model, gross housing wealth is a higher (lower) fraction of total wealth than in the data for the oldest (youngest) cohorts. The fact that we are abstracting from intergenerational altruism (that is, older cohorts exhaust their assets as they age) may account for the divergence for the oldest households. Other possibilities are limited availability of reverse mortgages in real life or uncertainty about health expenses in old age

[32]We use data from the Survey of Consumer Finances (averages from 1989 to 2004) instead of the PSID for these graphs, because the SCF has somewhat better information on wealth, and the sample sizes are larger, which are advantageous when examining different age groups.

which may result in higher liquid savings. The timing of accidental bequests (received early in life in the form of liquid wealth) could explain the divergence for the youngest cohorts.

Panel *(b)* in Figure A-4 depicts the life-cycle profile of homeownership rates in our benchmark calibration and in the data. Although we can reproduce the average U.S. homeownership rate, our model underestimates homeownership for ages 24 to 40, and overestimates homeownership rates for older cohorts, with the exception of the oldest. In our benchmark calibration, the oldest cohort turns to renting in the last period of life in order to free up forced housing equity.

It seems we would need further heterogeneity and/or additional assumptions to exactly replicate homeownership patterns and other profiles by age. However, this is not the focus of our paper. Our aim is to determine if our empirical findings are consistent with a story in which housing equity is used to alleviate liquidity constraints. To this end, we study the quantitative predictions of this model (with the key features of endogenous tenure choice and a collateral role for housing) regarding the effect of house-price changes on risk sharing.

Appendix G Alternative model specifications

Correlation between income shocks and house-price shocks

To allow for a possible correlation between income shocks and house-price shocks, we modify the income process by introducing a regional permanent shock, g_t, common to all residents of the region. Thus, $P_t = P_{t-1} g_t \gamma_t \epsilon_t \varsigma_t$, where $\log g_t \sim N\left(-\sigma_g^2/2, \sigma_g^2\right)$. To calibrate σ_g, we use the evidence in Luengo-Prado and Sørensen (2008). We save on state variables by assuming that the regional income shock and the house-price shock are perfectly correlated. This case can be seen as the opposite extreme from our baseline calibration in terms of income/house-price correlation. With this correlation, young households delay homeownership and the overall homeownership would be lower if the model was not recalibrated to match the same aggregates. See Figure A-5.

A bequest motive

We consider warm-glow altruism. The utility derived from bequeathing wealth, X_t, is:

$$v(X_t) = b \frac{X_t \left(\alpha^\alpha [(1-\alpha)/r_t^f]^{1-\alpha}\right)^{1-\sigma}}{1-\sigma},$$

where b measures the strength of the bequest motive, and terminal wealth equals the value of the housing stock, after depreciation takes place and adjustment costs are paid, plus financial assets: $X_t = q_t H_t (1-\delta^h)(1-\chi) + A_t$.

The Cobb-Douglas utility assumption we use as our benchmark would result in the inheritor's expenditure on nondurable consumption, C, and housing services, $r_t^f F_t$, in fixed proportions $\alpha/(1-\alpha)$. We consider bequests with and without correlation between income and house-price shocks. In this case, we have one additional calibration parameter, the strength of the bequest motive, so we add one additional target, the mean bequest-to-income ratio, set to 2.5 consistent with the evidence in Hendricks (2001).

Adding a bequest motive changes the results just slightly from the baseline regression—the direct effect of house prices is slightly larger reflecting that home owners hold on to their house longer rather than selling it in order to spend down life-cycle savings late in life (this makes the present value of adjustment costs lower)—see Figure A-5, panel (b) and Table A-6. One important difference is a significantly lower MPC out of income for renters when a bequest motive is at play. This is intuitive because, in the absence of a bequest motive, poor consumers (typically renters) would spend a higher fraction of increases in income. Importantly, our house-price interaction terms are consistently significant for owners, with a sign indicating risk sharing, while that is not the case for renters.

CES utility

We report results for a different utility function. In particular, we use the findings in Li et al. (2009), and consider a CES utility function with an intra-temporal elasticity of substitution between housing and nondurable consumption of 0.33 (i.e., housing and nondurables are complements).

In this case, the expenditure shares on housing and nondurables for renters are not independent of the relative price of the two goods, as in the Cobb-Douglas case. The parameter that controls the expenditure share on housing and nondurables, the discount rate, and the minimum house size are recalibrated to reproduce the same homeownership rate, wealth-to-income ratio, and ratio of house value to total wealth as in the case with a Cobb-Douglas utility function. The estimated coefficients using our simulated data are not very sensitive to this change. Most importantly, the house-price interaction term is positively significant for owners, indicating additional risk sharing, and not for renters—see Table A-6.

Appendix H Robustness to sampling frequency

We explore robustness of our results to the sampling frequency and report results in Table A-7. In the data, we find a somewhat stronger direct effect of house prices at the two-year frequency—especially for renters—and insignificant interaction terms. At longer frequencies the direct effect of house prices is fairly stable for owners and less so for renters although the effect remains significant. The direct effect of bad news does not vary much with the frequency indicating that disability and displacement indeed are persistent events. The interaction term is significant for 3-year and 6-year frequencies reaching its highest level of significance at the four-year frequency, the baseline. Our prior was that low frequencies would have low signal to noise ratios and the results bear this out but are otherwise robust.

In the model results are fairly robust to the sampling frequency except for the interaction term which becomes smaller as the sampling frequency increases. At long frequencies, people may be more likely to move anyway making the interaction effect smaller—the direct effects do not change with the sampling frequency as in the data.

Table A-1: Summary Statistics of Empirical Data

Variable	Mean	SD	Min	Max
$c_{it} - \bar{c}_t$	0.00	0.46	–1.84	1.69
$y_{it} - \bar{y}_t$	0.00	0.42	–2.22	2.04
$hp_{mt} - \overline{hp}_t$	0.00	0.13	–0.57	0.55
D_{it}	0.12	0.32	0.00	1.00
$(D_{it} - \bar{D}_t) \times (hp_{mt} - \overline{hp}_t)$	0.00	0.05	–0.47	0.46
L_{it}	0.02	0.28	–1.00	1.00
$(L_{it} - \bar{L}_t) \times (hp_{mt} - \overline{hp}_t)$	0.00	0.04	–0.55	0.55
BN_{it}	0.15	0.36	0.00	1.00
$(BN_{it} - \overline{BN}_t) \times (hp_{mt} - \overline{hp}_t)$	0.00	0.05	–0.44	0.43
Owner	0.60	0.49	0.00	1.00
Age	45.18	9.95	29.00	65.00

Notes: Variable definitions as follows: c_{it} is the (four-year) log difference of consumption for individual i in year t, y_{it} is the log difference of current income, and $\bar{c}_t$ ($\bar{y}_t$) is the mean log consumption (income) difference in period t. hp_{mt} is the log difference in house prices in the region where individual i lives, while $\overline{hp}_t$ is the mean log difference in house prices for all regions in period t. D_{it} is the displacement shock indicator; L_{it} is the limiting condition indicator; and BN_{it} is the "bad news" indicator.

TABLE A-2: SUMMARY STATISTICS OF SIMULATED DATA

Variable	Mean	SD	Min	Max
$c_{it} - \bar{c}_t$	0.00	0.22	–1.31	1.66
$y_{it} - \bar{y}_t$	0.00	0.58	–2.97	2.01
$hp_{mt} - \overline{hp}_t$	0.00	0.29	–0.37	0.35
D_{it}	0.15	0.36	0.00	1.00
$(D_{it} - \bar{D}_t) \times (hp_{mt} - \overline{hp}_t)$	0.00	0.10	–0.31	0.30
Owner	0.59	0.49	0.00	1.00
Age	45.65	11.07	28	64

Notes: Variable definitions as follows: c_{it} is the (four-year) log difference of consumption for individual i in year t, y_{it} (p_{it}) is the log difference of current (permanent) income, and $\bar{c}_t$ ($\bar{y}_t, \bar{p}_t$) is the mean log consumption (income) difference in period t. hp_{mt} is the log difference in house prices in the region where individual i lives, while $\overline{hp}_t$ is the mean log difference in house prices for all regions in period t. D_{it} is the displacement shock indicator.

Table A-3: IV Regression of Food on Nondurable Expenditures. CEX Data: 1980–2002

Log nondurable cons.	0.730***	Log nondurable cons. × HS	0.023
	(15.84)		(1.03)
Log nondurable cons. × 1980	0.122***	Log nondurable cons. × coll.	0.089***
	(9.45)		(3.72)
Log nondurable cons. × 1981	0.103***	Log regional food CPI	0.643***
	(9.09)		(3.88)
Log nondurable cons. × 1982	0.094***	Log regional fuel-util. CPI	–0.113***
	(8.87)		(–2.75)
Log nondurable cons. × 1983	0.089***	White	0.047***
	(8.78)		(6.91)
Log nondurable cons. × 1984	0.083***	Fam. size	0.055***
	(8.77)		(17.34)
Log nondurable cons. × 1985	0.081***	HS	–0.252
	(8.97)		(–1.22)
Log nondurable cons. × 1986	0.076***	Coll.	–0.924***
	(8.95)		(–4.10)
Log nondurable cons. × 1987	0.070***	Male head	0.082***
	(9.03)		(15.41)
Log nondurable cons. × 1988	0.067***	Married	–0.030**
	(9.55)		(–2.42)
Log nondurable cons. × 1989	0.061***	Age	0.012***
	(10.07)		(4.49)
Log nondurable cons. × 1990	0.051***	Age sq./100	–0.011***
	(10.05)		(–4.13)
Log nondurable cons. × 1991	0.043***	Born 1924–1932	–0.017*
	(9.51)		(–1.67)
Log nondurable cons. × 1992	0.041***	Born 1933–1941	–0.012
	(9.56)		(–0.90)
Log nondurable cons. × 1993	0.038***	Born 1942–1950	–0.004
	(9.52)		(–0.24)
Log nondurable cons. × 1994	0.034***	Born 1951–1959	0.001
	(9.64)		(0.06)
Log nondurable cons. × 1995	0.030***	Born 1960–1968	0.019
	(9.51)		(0.80)
Log nondurable cons. × 1996	0.023***	Born 1969–1978	0.029
	(8.92)		(1.02)
Log nondurable cons. × 1997	0.020***	Northeast	–0.013**
	(9.47)		(–2.33)
Log nondurable cons. × 1998	0.017***	Midwest	–0.061***
	(9.64)		(–11.48)
Log nondurable cons. × 1999	0.013***	South	–0.037***
	(8.57)		(–7.06)
Log nondurable cons. × 2000	0.011***	Constant	0.085
	(9.59)		(0.24)
Log nondurable cons. × 2001	0.006***	Adj. R sq.	0.721
	(7.58)		
N	40,630	F	1264.1

Notes: t-statistics in parentheses. Instruments for log nondurable consumption (and its interaction with year and education dummies) are the averages of log head's wages specific to cohort, education, and head's sex in a given year (and their interactions with year and education dummies). *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A-4: Risk sharing regressions—Data. Imputed Nondurables

	Owners		Renters	
Imputed nondurables				
House Price G.	0.144***	(4.48)	0.251***	(4.07)
Bad news	–0.050***	(–3.75)	–0.062**	(–2.42)
Bad news × House price G.	0.174*	(1.74)	0.098	(0.62)
No of obs.		14,274		6,168

Notes: See notes to Table 2.

Table A-5: Housing Equity and Consumption. Owners Only

	(1)	(2)
Bad news	–0.046***	–0.044***
	(–4.43)	(–4.19)
Bad news x House equity (lag)	–0.003	
	(–1.21)	
Bad news x House Price G.		0.187***
		(2.71)
Housing equity (lag)/10,000	–0.001*	–0.001*
	(–1.95)	(–1.87)
House Price G.	0.124***	0.123***
	(5.53)	(5.56)
Fam. size G.	0.338***	0.338***
	(25.31)	(25.35)
Age	–0.008**	–0.008**
	(–2.59)	(–2.57)
Age sq./100	0.004	0.004
	(1.27)	(1.25)
Adj. R sq.	0.080	0.081
F	160.6	158.6
N	17624	17624

Notes: Sample is restricted to owners defined as follows. Owners are households who continuously owned a house between years t and $t-4$, resided in the same MSA and did not change family composition during that time span. "Housing equity (lag)" is the level of housing equity at $t-4$; observations on housing equity above the 99th and below the 1st percentiles are dropped from the sample. Robust standard errors in the regressions clustered by the MSA where the household lives between years t and $t-4$. t-statistics in parentheses.
*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A-6: Risk sharing regressions–Model. Alternative Calibrations

	Owner		Renter	
Baseline				
Income G.	0.12***	(158.59)	0.30***	(186.42)
House Price G.	0.27***	(180.72)	0.01	(1.60)
Bad news	–0.10***	(–82.99)	–0.08***	(–36.33)
Bad news × House price G.	0.07***	(17.32)	–0.02**	(–2.10)
No. of obs.		151,150		62,126
		151,150		62,126
Bequest motive				
Income G.	0.12***	(188.10)	0.21***	(188.35)
House Price G.	0.29***	(169.01)	0.01**	(2.68)
Bad news	–0.10***	(–82.72)	–0.09***	(–46.63)
Bad news × House price G.	0.08***	(19.62)	–0.00	(–0.28)
No. of obs.		142,923		66,002
Bequest and income/house price correlation				
Income G.	0.12***	(170.73)	0.20***	(141.65)
House Price G.	0.39***	(301.98)	0.14***	(54.28)
Bad news	–0.10***	(–77.24)	–0.09***	(–45.77)
Bad news × House price G.	0.06***	(15.34)	–0.00	(–0.60)
No. of obs.		140,264		73,633
CES utility				
Income G.	0.10***	(87.48)	0.31***	(177.74)
House Price G.	0.28***	(146.37)	0.01	(1.33)
Bad news	–0.10***	(–88.93)	–0.08***	(–30.07)
Bad news × House price G.	0.06***	(18.04)	–0.02***	(–2.89)
No. of obs.		151,866		53,955

Notes: We run the following regression: $c_{it} - \bar{c}_t = \mu + \beta\ (hp_{mt} - \overline{hp}_t) + \xi\ (D_{it} - \bar{D}_t) + \zeta\ (D_{it} - \bar{D}_t) \times (hp_{mt} - \overline{hp}_t) + (X_{it} - \bar{X}_t)'\delta + \alpha(y_{it} - \bar{y}_t)\varepsilon_{it}$. We report the estimated coefficients $\hat{\alpha}$, $\hat{\beta}$, $\hat{\xi}$ and $\hat{\zeta}$. We control for age and age sq. in the regressions. All models recalibrated to match the same targets as benchmark. Serial correlation in the regression errors is corrected using the Prais-Winsten transformation; robust standard errors in the regressions clustered by region. t-statistics in parentheses. ***(**)[*] significant at the 1(5)[10]% level.

Table A-7: Risk sharing regressions–Data and Model. Different frequencies

	Owner		Renter	
Data				
Baseline				
House Price G.	0.135***	(5.92)	0.213***	(4.86)
Bad news	–0.047***	(–4.66)	–0.070***	(–4.09)
Bad news × House price G.	0.184***	(2.61)	0.012	(0.11)
No of obs.		19,228		8,776
2-year frequency				
House Price G.	0.162***	(6.04)	0.199***	(3.61)
Bad news	–0.036***	(–3.28)	–0.052***	(–3.66)
Bad news × House price G.	0.094	(0.98)	0.096	(0.54)
No of obs.		26,672		14,852
3-year frequency				
House Price G.	0.134***	(5.09)	0.110*	(1.87)
Bad news	–0.040***	(–3.84)	–0.082***	(–5.18)
Bad news × House price G.	0.182***	(2.87)	–0.077	(–0.61)
No of obs.		18,254		9,935
6-year frequency				
House Price G.	0.127***	(4.85)	0.239***	(4.41)
Bad news	–0.047***	(–4.20)	–0.059***	(–3.47)
Bad news × House price G.	0.116*	(1.89)	–0.027	(–0.27)
No of obs.		13,804		5,626
Model				
Baseline				
House Price G.	0.27***	(140.39)	0.01	(1.56)
Bad news	–0.17***	(–120.89)	–0.21***	(–69.05)
Bad news × House price G.	0.08***	(16.69)	–0.01	(–0.91)
No. of obs.		151,150		62,126
2-year frequency				
House Price G.	0.28***	(158.45)	0.01**	(2.57)
Bad news	–0.16***	(–146.20)	–0.24***	(–77.83)
Bad news × House price G.	0.14***	(18.24)	–0.07***	(–3.13)
No. of obs.		151,150		62,126
6-year frequency				
House Price G.	0.27***	(147.14)	0.01*	(1.72)
Bad news	–0.16***	(–76.69)	–0.18***	(–47.70)
Bad news × House price G.	0.06***	(11.36)	–0.00	(–0.04)
No. of obs.		151,150		62,126

Notes: We run the following regression: $c_{it} - \bar{c}_t = \mu + \beta\,(hp_{mt} - \overline{hp}_t) + \xi\,(D_{it} - \bar{D}_t) + \zeta\,(D_{it} - \bar{D}_t) \times (hp_{mt} - \overline{hp}_t) + (X_{it} - \bar{X}_t)'\delta + \varepsilon_{it}$. We report the estimated coefficients $\hat{\beta}$, $\hat{\xi}$ and $\hat{\zeta}$. We control for age and age sq. (and family size growth in PSID data) in the regressions. Serial correlation in the regression errors is corrected using the Prais-Winsten transformation; robust standard errors in the regressions clustered by region. t-statistics in parentheses. ***(**)[*] significant at the 1(5)[10]% level.

Figure A-1: MSA house-price appreciation (four-year growth rates)

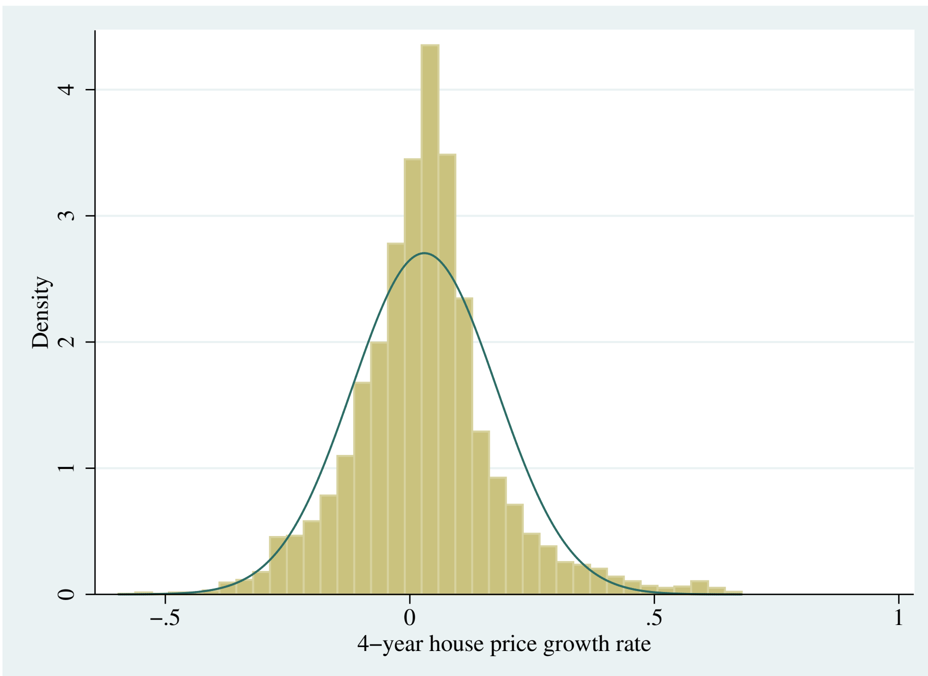
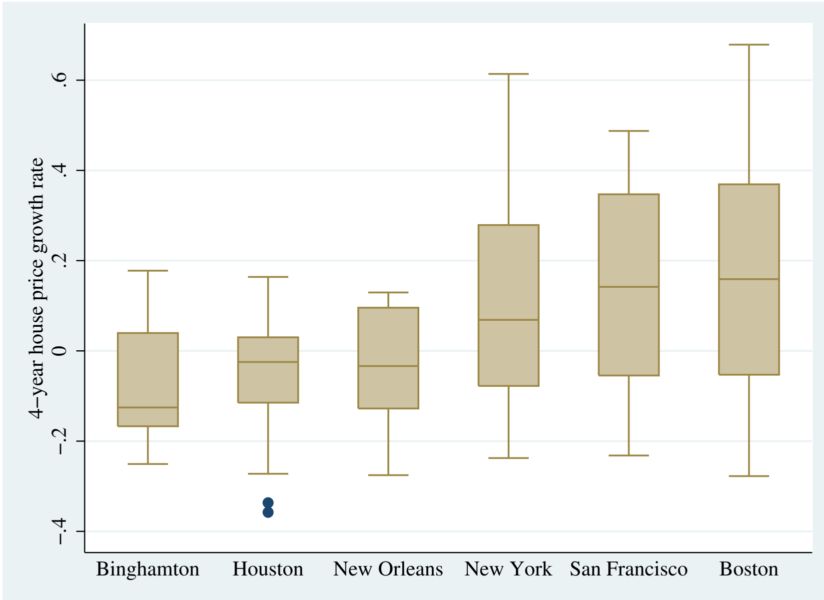


FIGURE A-2: MSA house-price appreciation. Selected MSAs

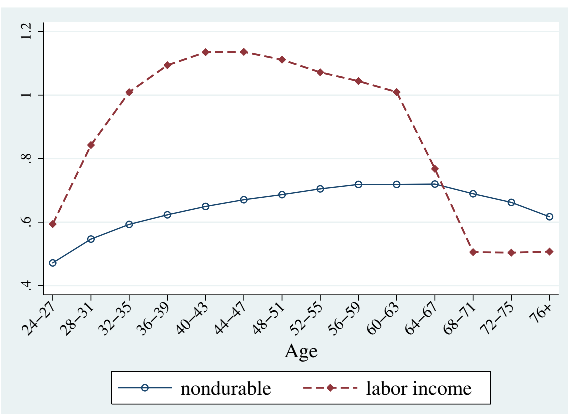


(a) Low vs. High

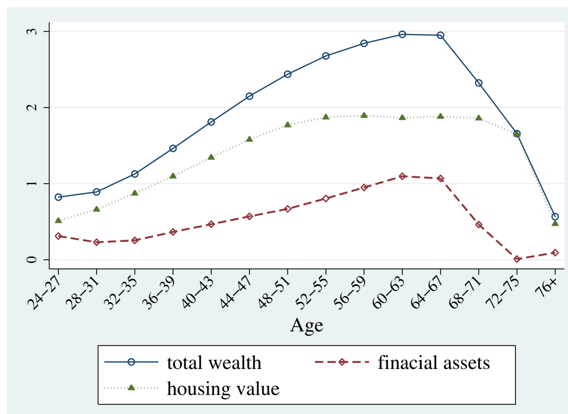
On each box, the central mark is the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data points not considered outliers, and outliers are plotted individually.

(b) Over Time

Figure A-3: Life-cycle Profiles. The Benchmark Case

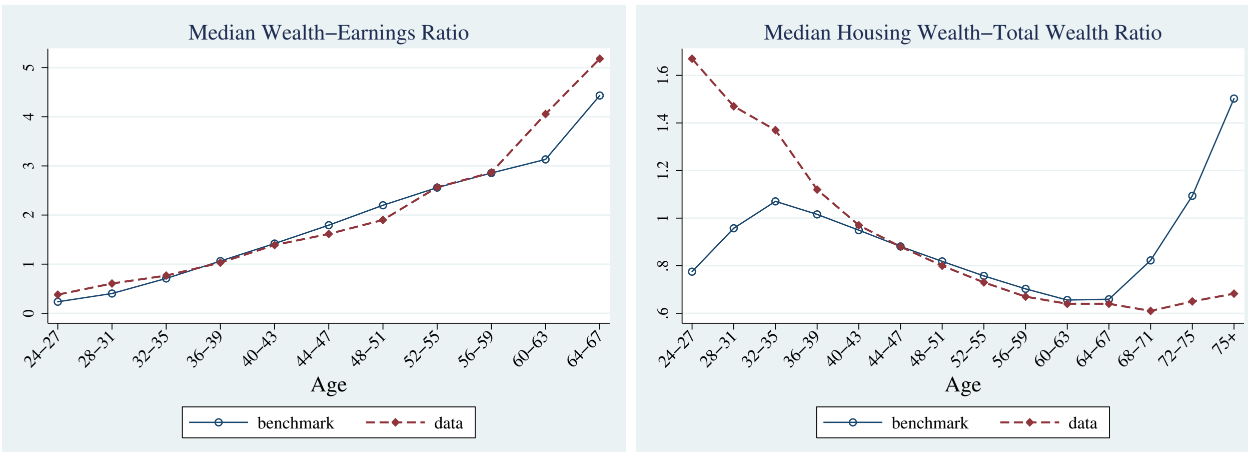


(a) Income and Consumption

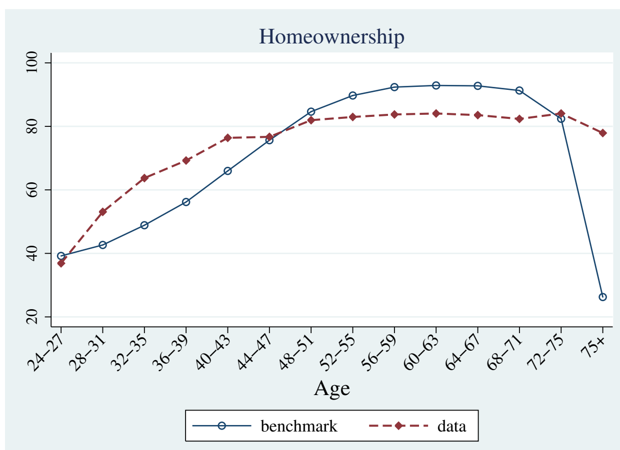


(b) Wealth

Figure A-4: The Benchmark and the Data

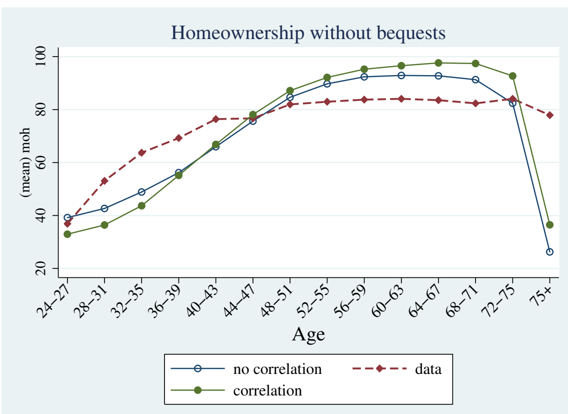


(a) Wealth and Earnings

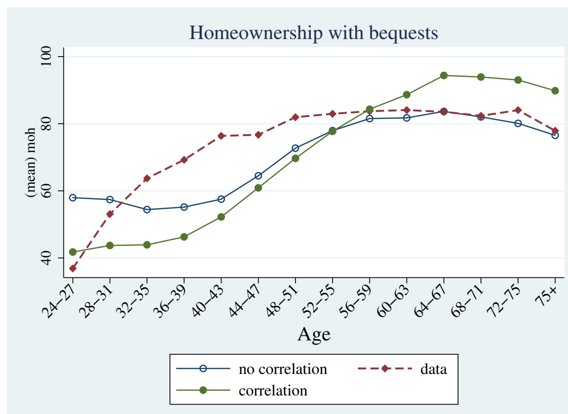


(b) Home ownership

Figure A-5: Home ownership under Different Assumptions



(a) Accidental Bequests



(b) Bequest Motive