Internet Appendix for

“Reverse Mortgage Loans: A Quantitative Analysis”

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This Internet Appendix provides details on the baseline model and counterfactual experiments in the article "Reverse Mortgage Loans: A Quantitative Analysis". Section I describes how we model household size dynamics. Section II discusses in detail our calibration, including the first-stage and second-stage estimation, and the third-stage calibration of reverse mortgage parameters. Section III presents additional facts on the distribution of debt in the calibrated baseline model. Sections IV and V describe the age profiles of homeownership rates, mean total assets, housing assets and financial assets, as well as the proportion of retirees in debt, for the baseline models with reverse mortgages, as well as for the models in the counterfactual experiments.

I. Household Size Dynamics in the Model

We incorporate household size into the model, as existing research on housing decisions in retirement, such as Venti and Wise (2004), finds that death of a spouse is often a trigger for selling the house and downsizing. We model household size transition as parsimoniously as possible, however, because it is not feasible to keep track of the health status of both spouses in a two-person household. Specifically, a household is either single ($s = 1$) or a couple ($s = 2$). Household size changes following a Markov transition probability $\pi^s_{i,s,s'}$. For an age-i couple household, the probability of losing a spouse and becoming single is $\pi^s_{i,2,1}$. With probability $\pi^s_{i,2,2} = 1-\pi^s_{i,2,1}$, the couple household remains a couple. We assume that a single household remains single with probability one, that is,

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$\pi^s_{i,1,1} = 1, \forall i$, to avoid consolidation of wealth when two singles get married and because our HRS data show that remarriage in retirement is rare. We also assume that when a household in the model dies, both spouses die. Since the probability of losing a spouse is lower than the probability of death for the majority of relatively younger households, couple households are more likely to become single before dying.

When we convert the type distribution in the HRS data to a model input, we assign age (i) and health status (m) to a couple household as follows. Since the husband and wife can differ in both age and health, we split each couple household in the HRS data into two households in the model. We then assign the age and health status of one of the spouses to each of the two households. Each of the two model households is then assigned one-half of the sample weight of the original household.

Household size s affects households in the following ways:

1. Pension income is multiplied by χ_s. For a single household, $\chi_1 = 1$. For a couple household, χ_2 is calibrated to be 1.48, which is the median value in the HRS data (see Section I.A.6 below). The consumption floor is multiplied by the same income multiplier.

2. For a couple household, consumption is shared but the consumption equivalence scale $\psi_2 = 1.34$ is below 2, which implies that there is a positive externality of being a couple. Moreover, $\psi_2 < \chi_2$, which implies that, everything else (including per-adult pension income) equal, per-adult consumption is higher for couple households.

3. Medical expenses in the model (x) represent household-level total medical expenses. Naturally, we assume that the distribution of medical expense shocks depends on household size s and estimate the parameters characterizing the distribution accordingly.

Table IAI
Household Size Transition

This table shows two-year transition probabilities of household size, in percent, conditional on current household size and age. The first two columns show the transition probabilities for two-person households, while the third and fourth columns are for single households. By assumption, single households remain single, which is a reasonable approximation of the data. These probabilities are constructed using HRS data pooled over the period 1996 to 2006.

	Current Period: Two-Adult		Current Period: One-Adult	
Age	One-adult	Two-adult	One-adult	Two-adult
65	3.38	96.62	100.00	0.00
75	8.00	92.00	100.00	0.00
85	13.41	86.59	100.00	0.00
95	21.85	78.15	100.00	0.00

Figure IA1. Household size distribution. This figure shows the proportion of single and couple households, conditional on age. The proportions are constructed based on the transition probabilities computed using HRS data pooled over the period 1996 to 2006.

II. Calibration in Detail

A. First-Stage Estimation

In the first-stage estimation, we set values of parameters that can be directly observed from the data. For the most part, our data source is the HRS.

A.1 Household Size

Table IAI shows the two-year transition probabilities of household size, conditional on ages 65, 75, 85, and 95. As with other shock processes, we assume that the household size transition prob-

Table IAII
Health Status Transition

This table shows two-year transition probabilities of health status, in percent, conditional on the current health and age of the household. The transition probabilities include mortality rates, captured as transition probabilities into the death state, which is absorbing. The table only shows transition probabilities for selected age groups, but transition probabilities are constructed for each model age using HRS data pooled over the period 1996 to 2006.

Health Status Transition (Age 65)				
	Dead	Excellent	Good	Poor
Excellent	1.3	72.8	21.5	4.4
Good	2.2	25.8	53.3	18.7
Poor	9.6	6.1	20.7	63.7

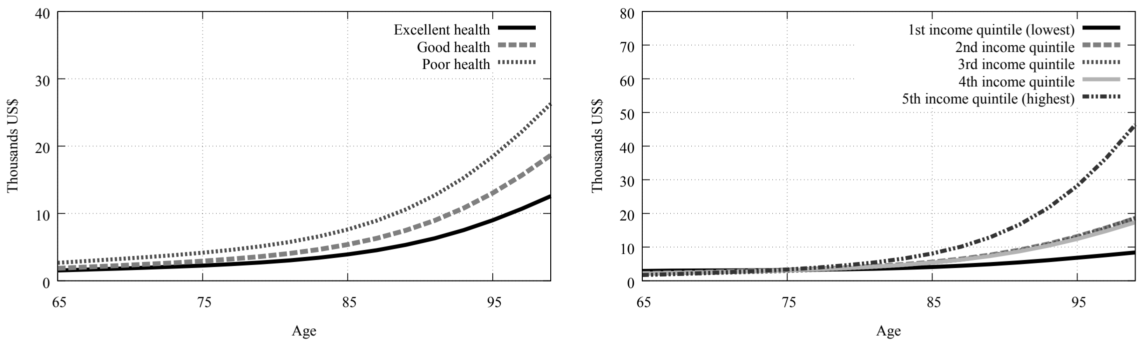
Health Status Transition (Age 75)				
	Dead	Excellent	Good	Poor
Excellent	3.9	60.1	26.9	9.2
Good	6.6	21.1	46.9	25.4
Poor	16.3	3.8	17.6	62.3

Health Status Transition (Age 85)				
	Dead	Excellent	Good	Poor
Excellent	10.5	46.8	27.1	15.6
Good	14.7	17.0	37.8	30.5
Poor	28.8	5.1	13.2	52.9

Health Status Transition (Age 95)				
	Dead	Excellent	Good	Poor
Excellent	28.5	29.5	19.8	22.3
Good	32.9	12.9	26.8	27.5
Poor	56.9	4.2	13.6	25.2

abilities are time-invariant and estimate them from the pooled 1996 to 2006 sample of the HRS. As can be seen in the last two columns of the table, we abstract from remarriages, based on a low occurrence of remarriages among retirees in our data; thus, a single retired household cannot become a couple again. We also assume that all the transitions from two- to one-adult households are caused by the death of the spouse and hence are involuntary, that is, we assume away divorce, which is rare in our sample. Figure IA1 presents the resulting proportions of two-adult and one-adult households conditional on age. The proportion is constructed using the initial (age-65) distribution of one-adult and two-adult households in HRS 2006 and applying the transition probabilities shown in Table IAI. The proportion of couples is approximately linearly decreasing with age, while the proportion of single households is, correspondingly, increasing.

The parameter ψ_s is the household consumption equivalence scale, which captures the positive externality enjoyed by couple households. We normalize $\psi_1 = 1$ and set $\psi_2 = 1.34$ for two-adult households, as computed by Fernández-Villaverde and Krueger (2007).



Panel A. Median Income, by Health Panel B. Good Health, by Income

Figure IA2. Expected mean out-of-pocket medical expenditure. The figure shows expected mean out-of-pocket medical expenditures, denominated in thousands of 2000 US$, for selected household types. The parameters of the distribution of medical expenditures are estimated using HRS data pooled over the period 1996 to 2006. Panel A shows mean medical expenses conditional on current household health status and age, for single households with median income. Panel B shows mean medical expenses conditional on income quintile and age for single households with good health.

A.2 Health Status and Mortality Risk

We group the five self-reported health states in the HRS into three categories: excellent, good, and poor. We also add death as one of the health states. We then compute two-year transition probabilities across health states, including probability of death, using the HRS pooled over 1996 to 2006, after observing that these probabilities are constant over this period. Table IAII shows the resulting transition probabilities for people aged 65, 75, 85, and 95. As expected, the mortality rate is higher for older and less healthy households. Health status is generally persistent, but the persistence weakens with age as health deteriorates on average.

A.3 Medical Expenditures

Our measure of out-of-pocket (OOP) medical expenses in the data includes both healthcare and long-term care (LTC) expenses, and we use the exit waves of the HRS to include end-of-life medical and LTC expenses, as in De Nardi, French, and Jones (2010). We estimate the distribution of log-OOP medical expenses as a function of age, health, household size, and income quintile, from the pooled HRS sample of retirees. The mean, standard deviation, and probability of zero expenses are estimated as quartics in age, and include interaction terms between age and the

Table IAIII
Probability of Permanent Nursing-Home Move

This table summarizes the two-year transition probabilities, in percent, of a homeowner being forced to move into a nursing home, conditional on the age and current health of the household. The probabilities are constructed using HRS data pooled over the period 1996 to 2006.

	Health Status		
Age	Excellent	Good	Poor
65	0.08	0.14	0.18
75	0.42	0.42	1.04
85	1.50	2.41	4.83
95	8.43	8.43	16.50

other three variables. Under the assumption of log-normality of medical expenses, we compute the expected mean and standard deviation of medical expenses in levels. The probability of zero medical expenses is used to ensure that the types of households that do not pay OOP in the data are not incorrectly allocated OOP shocks in the model. Figure IA2 reproduces expected mean medical expenses for single households in the middle income bin by health (Panel A), and for single households in good health by income bin (Panel B). As we would expect, people in worse health have higher expenses, as do those with higher income, and OOP expenses grow dramatically with age, especially for higher-income individuals. The implication of our calibration is that a 91-year-old single individual with median income and in poor health has a 5.6% chance of spending $102,506 out of pocket per (two-year) period, in 2000 dollars. A similar individual who is 95 has a 5.5% chance of spending $154,650 in two years, while her high-income counterpart would have a 6% chance of spending $337,610 in two years. These numbers are in line with the findings in Ameriks et al. (2011).

A.4 Compulsory Nursing Home Moves

Using the HRS sample pooled over 1996 to 2006, we compute the two-year probability that a homeowner moves into a nursing home *and* simultaneously stops being a homeowner, conditional on the household's age and health status. This probability is important to consider, since moving out of the house requires selling the house and repaying the reverse mortgage. In computing this measure, in the data we consider only *permanent* moves to nursing homes concurrent with the loss of homeownership, using the panel dimension to identify such moves. We interpret these moves as involuntary. Table IAIII shows these probabilities for ages 65, 75, 85, and 95. Not surprisingly, the probability is higher for less healthy individuals and grows rapidly with age. There are two caveats to these estimates. First, not all permanent moves into nursing homes are involuntary in the data. This implies that our measure of the probability that a household is forced to move out is biased upward, which causes the estimate for extra utility of homeownership to be biased upward. On the other hand, some older retirees might move to their children's homes instead of a nursing home. This consideration implies that the probability of a moving shock might be underestimated. The data limit how well we can identify these events; our estimates of the moving shock are the best that the data allow.

A.5 Housing, Conventional Mortgages, and Interest Rates

We allocate self-reported house values in our 2006 sample of 65-year-olds equally into 11 bins, and compute the median value of each bin to create a discrete house value distribution. Housing requires maintenance, whose cost is a fraction δ of the house size. We set δ to 1.7% per year, which is the average depreciation rate of residential structures in National Income and Product Accounts (NIPA). When a household sells the house, the sales cost, which is a fraction κ of the house value, has to be paid. We set the sales cost of a house (κ) to 6.6% of the value of the house. This is the estimate obtained by Greenspan and Kennedy (2007). Grueber and Martin (2003) find a median selling cost of 7.0% of the value of the house.

The interest rate is set at 2.58% per year. For conventional mortgage loans, we assume a borrowing premium (ι^m) of 1.69% annually. This is the average spread between 30-year conventional mortgage loans and 10-year Treasury bonds between 1996 and 2006.[1] Following the arbitrage condition standard in the literature, we assume that rent is the sum of maintenance costs and the

[1] We use 10-year Treasury bonds because the average life of a 30-year mortgage in the U.S. is 7 to 10 years.

conventional mortgage interest rate: $r_h = \delta + r + \iota^m$.

The collateral constraint for conventional mortgage loans is computed based on equation (10), which states that the expected debt service obligation never exceeds the share α of the household's income. In the data, mortgage lenders impose two types of debt-to-income (DTI) ratio. The first is the front-end DTI ratio, which is applied only to mortgage and housing related expenses, such as mortgage, insurance, and property tax payments. The front-end DTI ratio is typically around 30% to 35%. The second is the back-end DTI ratio. The back-end DTI ratio includes not only payments included in the front-end ratio, but also the payment of unsecured debt, student loans, and the like. The back-end DTI ratio is typically 43%. Since households in the model are retirees and are not likely to pay for student loans, and they carry a relatively small balance of credit card debt, we model only equity debt and choose $\alpha = 0.35$.

Figure 6 for the resulting collateral constraints shows $\lambda^m_{i,b,s,m,p}$ in the model. Households with lower income and older households have more restricted access to conventional mortgages. This aligns well with the findings of, for instance, Caplin (2002), who points out that most retirees fail the income requirements of conventional mortgage contracts and thus are unable to borrow in that way.

To calibrate idiosyncratic house price shocks, we assume that the house price is normalized to one in the initial period and follows an AR(1) process thereafter. To estimate the AR(1) process, we use CoreLogic HPI, which is a proprietary and confidential monthly ZIP code-level home price index. ZIP code-level granularity is sufficiently rich for our purposes, absent data on individual house prices over time. The CoreLogic HPI is a monthly repeat-sales single-family house price index, available from January 1976 to March 2015. For each ZIP code, the index is normalized to 100 in January 2000. Since we use all sales transactions, including distressed sales, short sales, and real estate owned (REO) properties, we obtain house price data for 7,142 ZIP codes.[2] According to CoreLogic, the index covers 57.3% of the U.S. population. Since one period is two years in our model, we first construct biennial data by simple averaging after deflating the data using the CPI.

[2]We also run our regression excluding distressed sales, short sales, and REO and find that our regression results change little.

Table IAIV
Income Levels

This table presents annualized after-tax nonfinancial income of households in quintiles, denominated in 2000 US$. The quintiles are used in the model as five different levels of nonfinancial income. The income bins are computed using the 2006 wave of the HRS.

Group	Group 1	Group 2	Group 3	Group 4	Group 5
Income	6,858	12,404	17,948	25,918	42,722

We then run the following regression with the ZIP code-level biennial data:

$$\log p_i' = \bar{p} + \rho_p \log p_i + \epsilon, \tag{IA1}$$

where $\epsilon \sim N(0, \sigma_p^2)$, i indicates the ZIP code, $\bar{p}$ denotes the average level of house prices, ρ_p is the persistence in the real house price index, and σ_p is the standard deviation of the house price innovation. The regression yields $\rho_p = 0.859$ and $\sigma_p = 0.125$. We use these parameter values for our calibration of the idiosyncratic house price shock. The adjusted R^2 is 0.764. To translate this estimation into the model, we discretize the AR(1) process into a biennial first-order Markov process. The resulting shocks are large, fluctuating between -29% and 41% of the median house value. The shocks are also persistent. For example, when the house price is 41% above the median level, the expected duration of staying at that level is 6.7 years. [YAH]

A.6 Nonfinancial Income

We group nonfinancial income into five bins, as summarized in Table IAIV. We define nonfinancial income to include Social Security, pension, disability, annuity, and government transfer income, net of taxes. Because some of our retirees are only partly retired, we also include labor income in this measure. However, labor income plays a small role in our sample, constituting on average 6% of total income. We compute the nonfinancial income of households aged 63 to 67 in the 2006 HRS sample ("age 65" in our calibration), allocate them into five quintiles, and compute the median income in each quintile. Finally, we adjust nonfinancial income b using the household

Table IAV
Selected Characteristics of the Initial Distribution

This table summarizes selected characteristics of the initial, age-65, distribution of household types. The type distribution is constructed using the 2006 wave of the HRS and is used as the input for simulations in the baseline model.

Health Status		Tenure Status		Financial Asset Position	
1 (excellent)	0.445	Homeowner	0.885	Saver	0.792
2 (good)	0.323	Renter	0.115	Borrower	0.208
3 (poor)	0.231				

size adjustment factor χ_s in the budget constraint of the model. We measure χ_s from the fact that for the median in our sample, the income of a couple household is 1.48 times larger than the same household's income after one spouse dies; the standard deviation of this number is 0.8.

A.7 Initial Type Distribution

The type distribution of age-65 retired households is constructed using the HRS 2006 wave. By taking the initial distribution directly from the data into the model, we capture empirically relevant correlations across household characteristics, for example, the correlations between income, housing, and financial wealth, health, household size, and homeownership. Table IAV presents dimensions of the initial distribution that we have not already discussed. As can be seen, 45% of the households are in excellent health. The homeownership rate is close to 90%. All retirees in the sample are net savers. However, in the language of the model, the financial asset position includes secured debt. By this measure, 21% of our sample has a net negative position. [YAH]

B. Second-Stage Estimation: Comparison to Previous Estimates

Since in our previous work (Nakajima and Telyukova (2013)) we use a model that is related to the model used in this paper, in this section we compare the parameter estimates between the two models.

There are significant differences in terms of both the model and the data sample that we use to estimate the model. These differences are very likely to produce some differences in parameter estimates in the second-stage estimation. Nevertheless, many of the estimated parameters are similar across the two models. In particular, the consumption aggregator parameter η (0.76 here, 0.81 previously), coefficient of relative risk aversion σ (2.01 vs. 2.93 previously), and consumption floor per adult $\underline{c}$ (\$13,919 in 2000 dollars vs. \$8,981 in 1996 dollars) are all quite close to each other, considering the underlying differences in the focus, features, and methods in the two models.

The discount factor β is 0.91 in annual terms in the current model, compared to 0.98 in our previous model. This implies less patient households and affects household saving and debt. The difference likely stems from substantial differences in the models pertaining to the dynamics of housing prices. In particular, in Nakajima and Telyukova (2013), we model the 1996 to 2006 housing boom as the constant house price growth perfectly predicted by households. When households know that house prices are growing rapidly, a high discount factor is needed to prevent households from overborrowing, relative to the data, in order to front-load the capital gains of housing price appreciation.

Differences in how we model house price dynamics, as well as the financial benefits of homeownership, also generate the difference in the estimate of ω_1, which measures the extra utility of homeownership relative to renting. In the current model this parameter is 4.9, while in our previous model it is 2.5. In our previous work we model the trend in house price growth as well as some tax benefits of ownership, such as avoiding the capital gains taxation associated with selling the house. These features encourage homeownership, even with a relatively low value of ω_1 in our previous work, but are absent from the current model. Moreover, in the present model we have idiosyncratic house price shocks and nursing home move shocks, which create the impetus for selling the house whenever a high price shock is realized, or induce moving out involuntarily in the case of a move shock, both of which drive ω_1 up. The difference between the two parameter values indicates that the omitted financial forces, as well as idiosyncratic price and move shocks, play quantitatively important roles.

The most dramatic difference between the two models is in the calibration of bequest motives. The parameter γ, which measures the strength of the bequest motive, is nearly three times higher in the current model relative to the previous one, at 20.5 versus 7.2, At the same time, the luxury bequest parameter ζ is significantly smaller in this model (7,619) relative to our previous model (45,714), counteracting the difference in γ. The reason lies in part in the difference of the targets and hence in identification strategies. Because of our previous interest in studying the retirement saving puzzle itself, in the previous model we match net worth profiles by income bin. The bequest parameters in that model have to match the steep dissaving of lower-income groups late in life, which both decrease the strength of the bequest motive and increase the luxury bequest parameter. The distributions of debt, as well as bequests, are discussed in the text of this paper; we do not target the dissaving behavior of the low tail, which accounts for the changes in the bequest parameters.

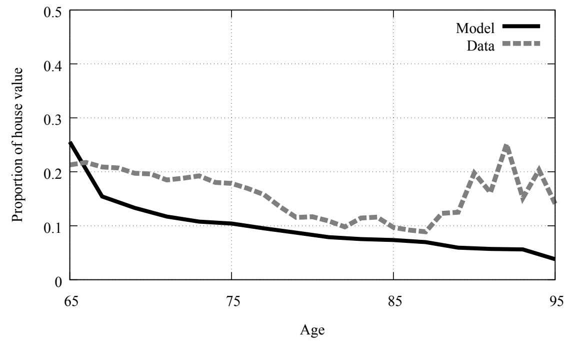
C. Third Stage: Calibration of Reverse Mortgage Parameters

To conduct our experiments, into the calibrated baseline model we introduce reverse mortgages. In order to calibrate parameters that characterize RMLs, we rely on the terms of reverse mortgage contracts in the data. The up-front and per-period costs associated with insurance against house price shocks are $\nu^i = 2.0\%$ and $\iota^i = 1.25\%$ per year, respectively. Reverse mortgages are further characterized by the triplet $\{\lambda_i^r, \iota^r, \nu^r\}$, which captures the collateral constraint, the interest premium, and the up-front cost. We set the interest premium of reverse mortgages to be the same as conventional mortgages at $\iota^r = 1.69\%$ annually.

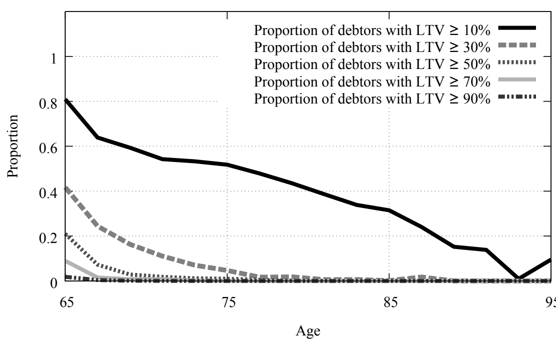
The up-front cost in the data appears to be about 5.0% of the house value. The origination fee is typically 2.0% of the house value up to $200,000 and 1.0% above it, with a cap of $6,000 and floor of $2,500. Considering that most house values in the model, as in the data, are below $200,000, but half of the houses are below $100,000 (where the floor of $2,500 binds), 2.5% is reasonable. Closing costs are typically around $2,000 to 3,000. Dividing this amount by the median house value in the sample, we get 2.5% as well. Adding these together, we get $\nu^r = 5.0\%$.

We calibrate the age-dependent collateral constraint λ_i^r for reverse mortgages from the HUD schedules of HECM credit line growth, given our assumed mortgage interest rate of 5.7% (see, for instance, AARP (2010)). These schedules imply that at age 65, a household can borrow 49.6% of their house value; by age 95, that number is 81.5%. The collateral constraint slackens with age because the remainder of home equity is reserved by the lender for repayment of expected interest and insurance costs that accumulate over the life of the loan; thus, the older the borrower is at the time of withdrawal from the credit line, the more credit she has access to. The entire collateral constraint schedule is the dashed line in Figure 6. It is easy to see the benefits of RMLs. While the collateral constraint associated with conventional forward mortgages tightens up with age, RMLs offer a collateral constraint that relaxes with age. The difference is more striking for homeowners with lower income and a larger house.

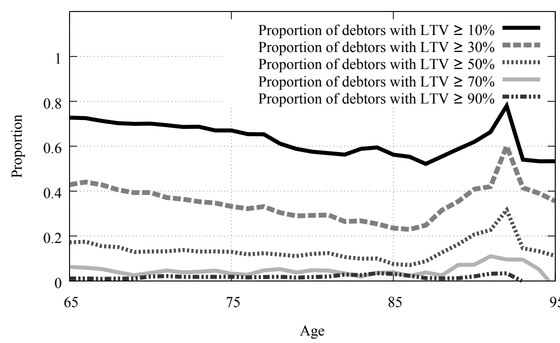
III. Additional Baseline Model Characteristics: Debt Distribution



Panel A. Median LTV Ratio



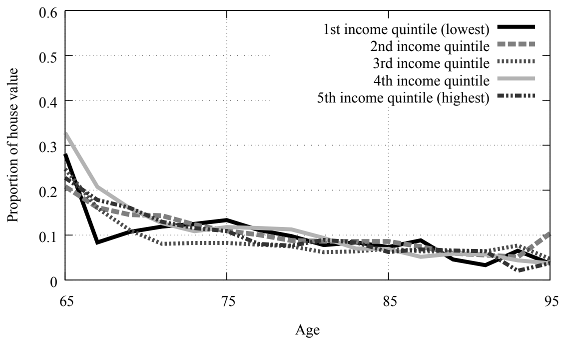
Panel B. Distribution of LTV Ratio, Model



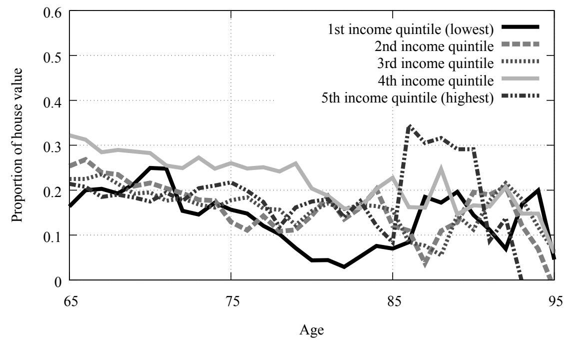
Panel C. Distribution of LTV Ratio, Data

Figure IA3. Model versus data: distribution of LTV ratio. These figures compare distributional statistics of the LTV ratio, conditional on age, between the model and the data. The model outputs are based on the simulation of the calibrated baseline model. The data profiles are constructed based on age-year regressions using HRS data pooled over the period 1996 to 2006.

Figure IA3 compares the median loan-to-value (LTV) ratios, as well as the distribution of LTV ratios, that is, shares of households with LTV ratio above 10%, 30%, 50%, 70%, and 90%, between the model and the data. The LTV ratio is just the level of debt as a share of house value. The median LTV ratio is decently matched by the model, although as we discussed before, the model predicts faster initial decumulation of debt than its empirical counterpart. This is also true when we look at the proportion of households with a LTV ratios above 10%, 30%, 50%, 70%, and 90% – the model implies that most households pay down debt faster than they do in the data, suggesting that the borrowing constraints are tighter in the model than the data. For example, over 30% of data households of age 75 have a LTV ratio greater than 30%, while the same share in the model is around 5%. At age 85, around 60% of households have a LTV ratio greater than 10%, while in the model that share is about 30%.



Panel A. LTV Ratio, Model

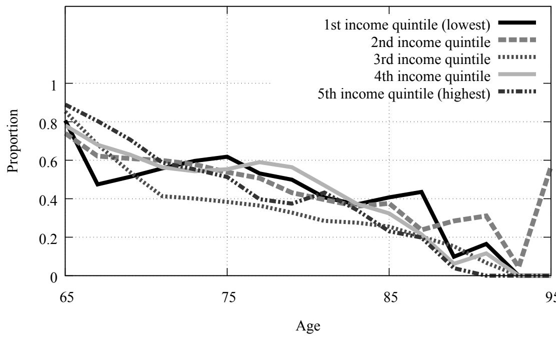


Panel B. LTV Ratio, Data

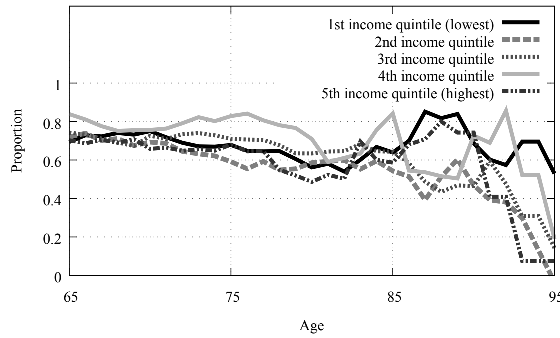
Figure IA4. Model versus data: LTV ratio, by income bin. These figures compare median LTV ratios by age for each income quintile between the model and the data. The model outputs are based on the simulation of the calibrated baseline model. The data profiles are constructed based on age-year regressions using HRS data pooled over the period 1996 to 2006.

Figure IA4 compares the median LTV ratios for each of the five income groups. They are consistent overall in both the model and the data, in the sense that the dispersion in life-cycle profiles of the LTV ratios across income groups is not that large, and the profiles have similar slopes for the majority of the life cycle. The LTV profiles are somewhat flatter in the data, due to a notable initial decline in the model that is not mirrored in the data.

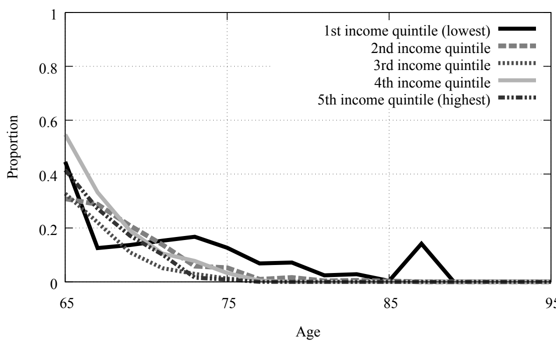
Figures IA5 and IA6 further break down the LTV distribution by showing households with each LTV ratio (higher than 10%, 30%, 50%, 70%, 90%) by income bin. As we would expect given the above discussion, the model predicts faster decumulation of debt than the data for all levels of LTV.



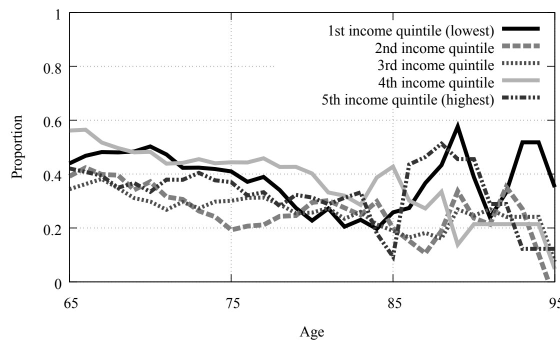
Panel A. Debtors with LTV ratio ≥ 10%



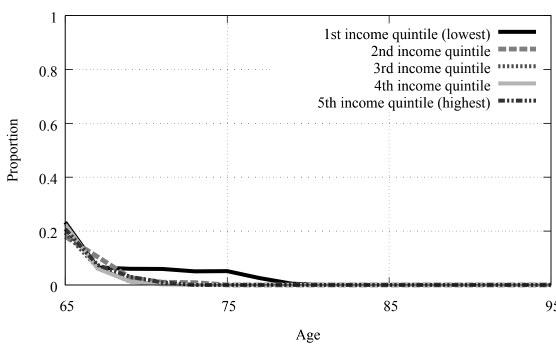
Panel B. Debtors with LTV ratio ≥ 10%



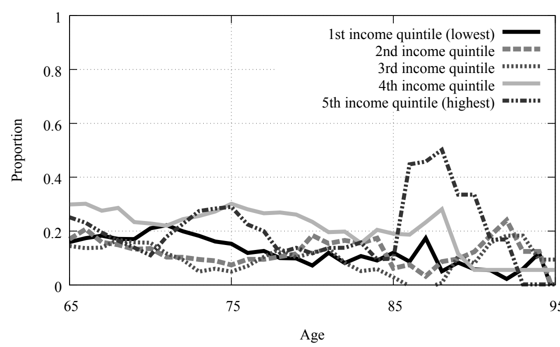
Panel C. Debtors with LTV ratio ≥ 30%



Panel D. Debtors with LTV ratio ≥ 30%

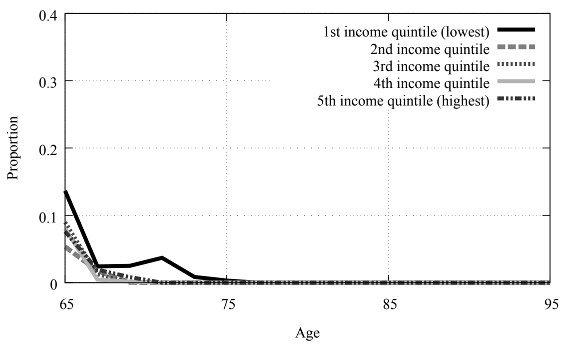


Panel E. Debtors with LTV ratio ≥ 50%

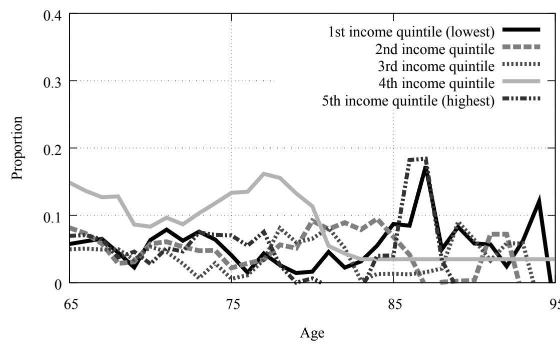


Panel F. Debtors with LTV ratio ≥ 50%

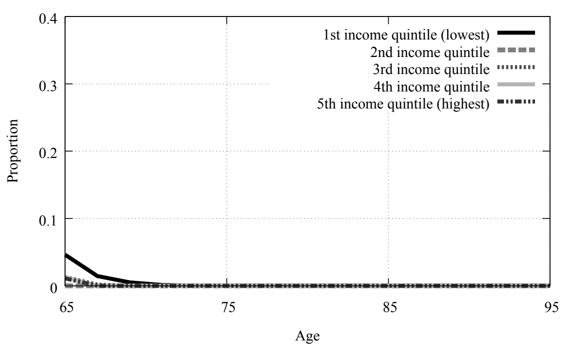
Figure IA5. Model (left) versus data (right): LTV ratio distribution by income bin. These figures compare the proportion of debtors with LTV ratio above 10%, 30%, and 50% by income quintile conditional on age between the model and the data. The model outputs are based on the simulation of the calibrated baseline model. The data profiles are constructed based on age-year regressions using HRS data pooled over the period 1996 to 2006.



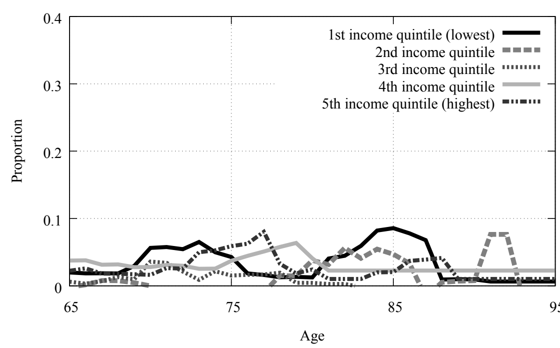
Panel A. Debtors with LTV ratio ≥ 70%



Panel B. Debtors with LTV ratio ≥ 70%

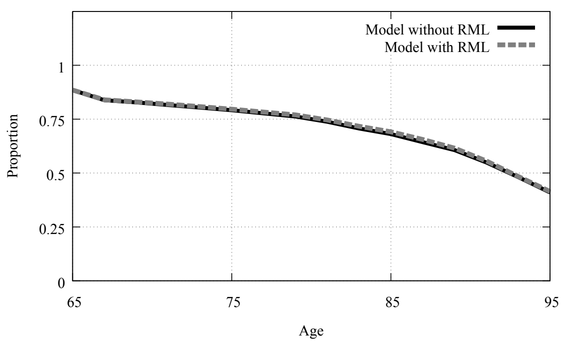


Panel C. Debtors with LTV ratio ≥ 90%

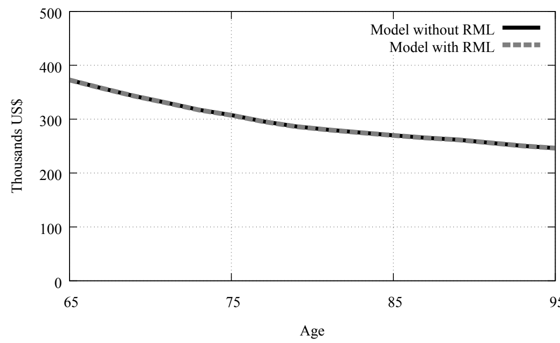


Panel D. Debtors with LTV ratio ≥ 90%

Figure IA6. Model (left) versus data (right): LTV ratio distribution by income bin. Continuation of Figure IA5, for LTV above 70% and 90%. See notes in Figure IA5.

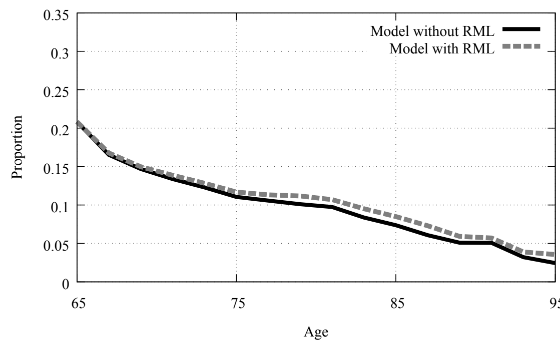


Panel A. Homeownership Rate



Panel B. Mean Total Assets

Panel C. Mean Housing and Financial Assets



Panel D. Proportion in Debt

Figure IA7. Age profiles in models with and without RMLs. The figures compare key age profiles of assets in the model without RMLs, which is the calibrated baseline model, to those in the model in which agents are given an option to purchase RMLs.

IV. Age Profiles in Model with Reverse Mortgages

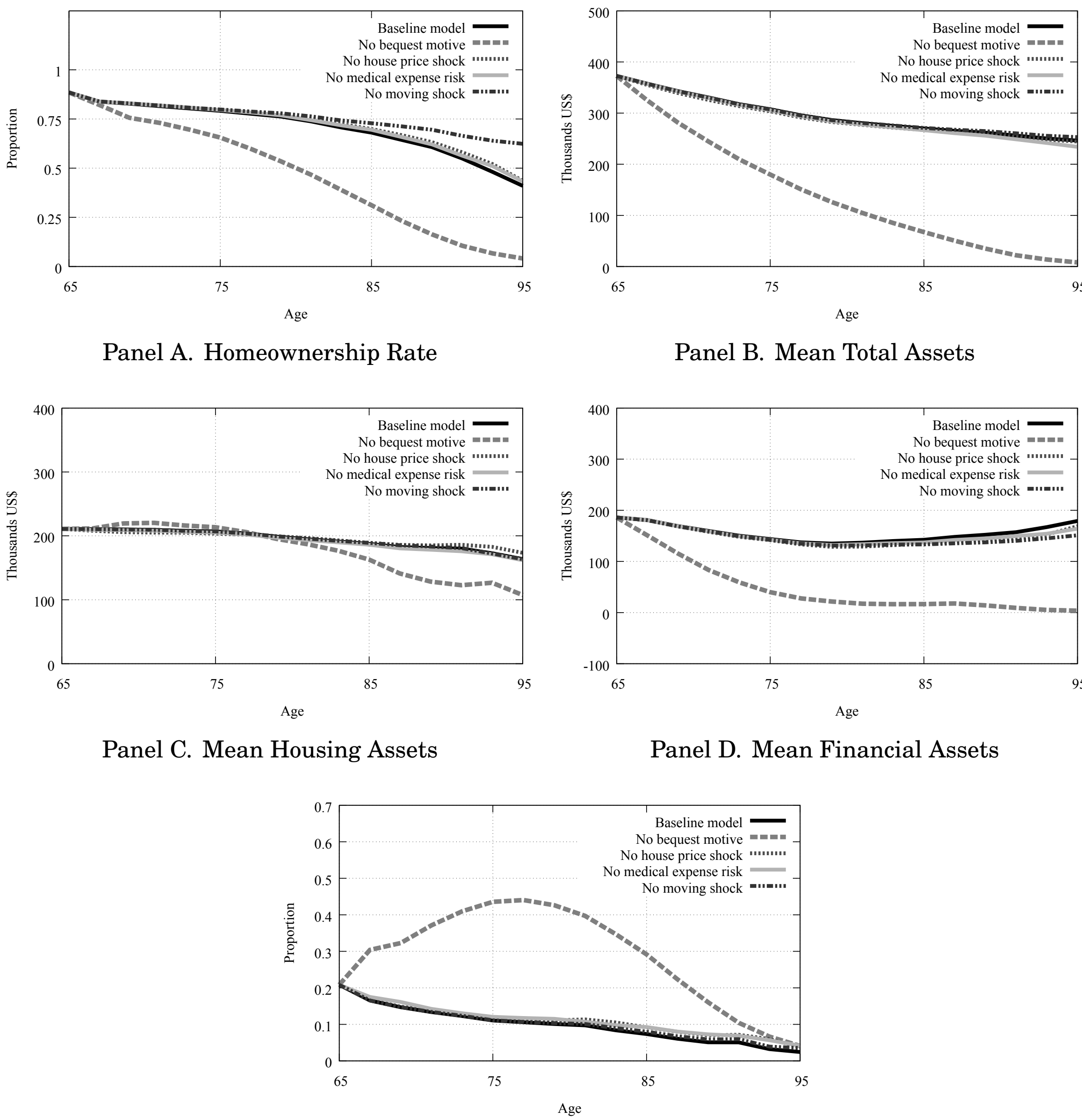
Figure IA7 shows the age profiles discussed previously, in the model with reverse mortgages relative to the benchmark without. Given the low take-up rate of reverse mortgages, the aggregate effect of reverse mortgages is small. Reverse mortgages enable people to stay in their house longer, which slightly raises the homeownership rate relative to the benchmark model, while increasing the proportion of homeowners in debt, which slightly decreases mean housing and financial assets.

V. Age Profiles in Experiment Economies

In this section, we include the age profiles that result from alternative economies in Section IV.C of the main article, where we investigate the impact of various risks and bequest motives in the baseline economy.

Figure IA8 demonstrates the age profiles in alternative models, where we shut down, in the benchmark model, bequest motives, house price shocks, medical expense risk, and nursing home moving shocks. The most notable difference comes from the model without bequest motives. As we previously discussed, the bequest motive is the strongest motivation for saving late in life, including through homeownership. Absent the bequest motive, the homeownership rate declines nearly to zero, in spite of the fact that the utility parameter on homeownership does not change. At the same time, while they own their homes, homeowners borrow against reverse mortgages significantly more, with borrowing activity peaking between ages 75 and 77. As a result, we also see a smooth decline in mean total assets and its components. A second notable difference comes from the economy with no nursing home moving shock. Not surprisingly, the absence of this shock means that retirees stay in their homes much later in life, with the homeownership rate profile becoming much flatter late in life. Consequently, the borrowing rate also increases, particularly at later ages.

Figure IA9 describes the effect of house price growth on the model's age profiles. With perpetually rising house prices, homeowners are encouraged to borrow against their homes earlier in life, in part to finance more consumption up-front. However, many homeowners sell their house later in life, because the collateral constraint for conventional mortgages does not adjust with house price growth. At some point, homeowners decide to tap into the (appreciated) house value by selling their house, when the collateral constraint, which depends purely on the repayment ability of homeowners and not on house value, starts to bind. As a result, in this economy there is less debt and financial assets are higher later in life, and the overall net worth profile stays flat, buoyed by the reduction in borrowing and ever-increasing house prices for those that stay owners. On the



Panel A. Homeownership Rate

Panel B. Mean Total Assets

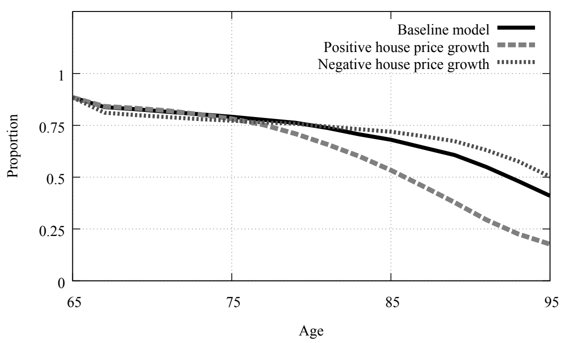
Panel C. Mean Housing Assets

Panel D. Mean Financial Assets

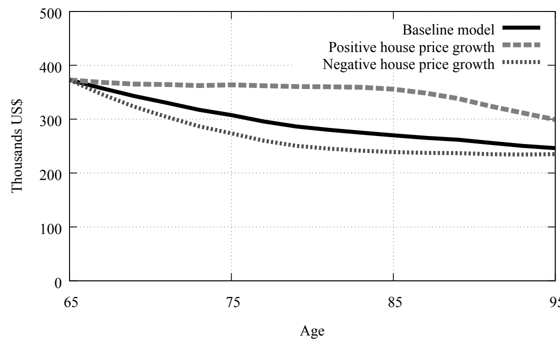
Panel E. Proportion in Debt

Figure IA8. Effects of a bequest motive and uncertainty. The figures compare key age profiles of assets in the baseline model with those from alternative models in which one of the main elements of the baseline model is turned off, in order to highlight the role that each element plays in the baseline. The alternative models are the model without a bequest motive, the model without a house price shock, the model without median expense risks, and the model without a compulsory moving shock.

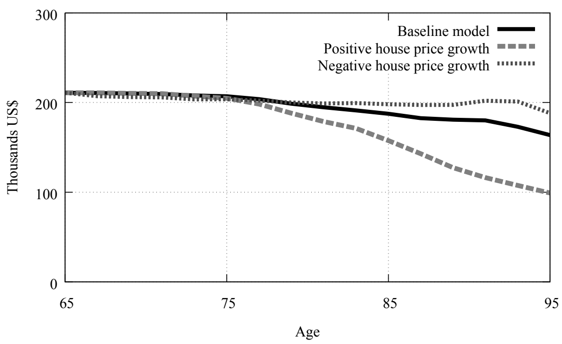
other hand, when house prices are perpetually falling, homeowners borrow less to back-load consumption. The homeownership rate remains higher in this economy because homeowners borrow less, which makes them less likely to be forced to sell their house in the face of a large medical expense shock. Mean total assets, however, are lower than in the baseline, reflecting capital loss



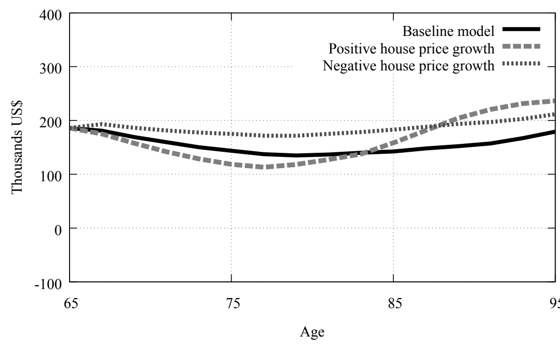
Panel A. Homeownership Rate



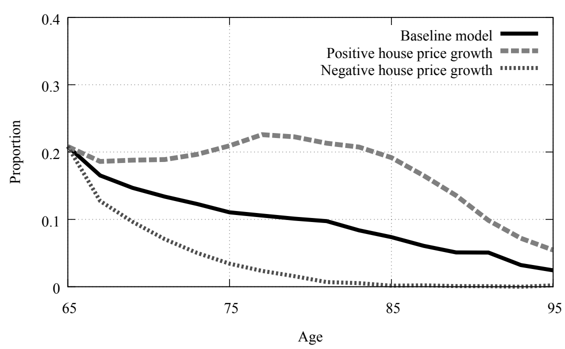
Panel B. Mean Total Assets



Panel C. Mean Housing Assets



Panel D. Mean Financial Assets



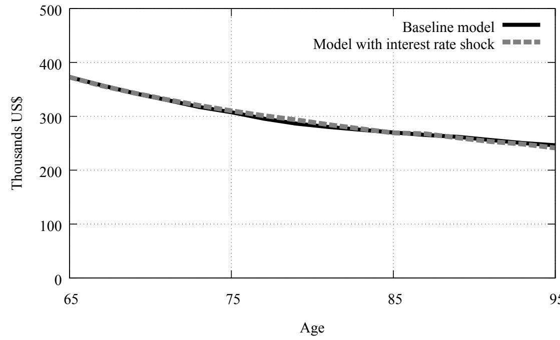
Panel E. Proportion in Debt

Figure IA9. Effects of house price growth. The figures compare key age profiles of assets in the baseline model with those from alternative models with positive or negative deterministic house price growth. The house price growth rates are 4.5% per year, positive or negative, motivated by the average house price growth rate in the U.S. during the recent house price boom.

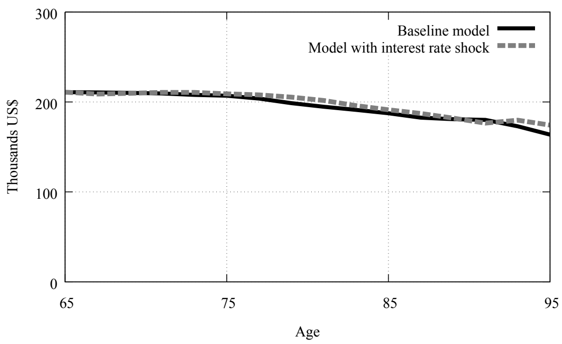
from house price depreciation.

Figure IA10 shows the life-cycle profiles of the alternative economy with interest rate risk. We find that adding this idiosyncratic shock does not alter the life-cycle profiles relative to the baseline model in a significant way.

Panel A. Homeownership Rate

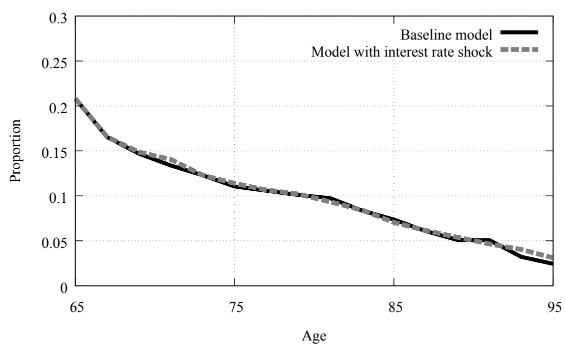


Panel B. Mean Total Assets



Panel C. Mean Housing Assets

Panel D. Mean Financial Assets



Panel E. Proportion in Debt

Figure IA10. Age profiles in the model with an interest rate shock. The figures compare key age profiles of assets in the baseline model with a fixed savings interest rate and the alternative model with interest rate shocks. Interest rate shocks affect the savings interest rate and the interest rate of RMLs, which tend to be adjustable rates, but not the interest rate of conventional mortgages, which tends to be a fixed rate.

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