ONLINE APPENDIX

Debt Portfolios and Homestead Exemptions*

Thomas Hintermaier and Winfried Koeniger

Abstract

This online appendix contains (i) information on the construction of the data for the wealth and debt portfolios as well as labor earnings based on the Survey of Consumer Finances, (ii) a detailed description of the calibration of the income process, (iii) the model predictions for the life-cycle profiles and (iv) results of robustness checks for higher loan-to-value ratios of 0.9 and 0.975.

*Hintermaier: University of Bonn, Department of Economics, Adenauerallee 24 - 42, 53113 Bonn, Germany, thomas.hintermaier@uni-bonn.de; Koeniger: University of St.Gallen, Department of Economics, SEW-HSG, Varnbuelstrasse 14, 9000 St.Gallen, Switzerland, winfried.koeniger@unisg.ch.

A Data appendix

This data appendix describes how we construct data counterparts for the wealth and debt portfolio as well as labor earnings in the model, using data from the Survey of Consumer Finances (SCF). Since the questions in the SCF survey refer to income in the previous year and agents have made their consumption and portfolio choices conditional on this income, we interpret the SCF asset data as end-of-period information at the time when the survey is carried out. We construct all variables for the full SCF sample and then apply the sample-selection criteria mentioned below. When computing the statistics in the data, we use the sampling weights provided in the SCF. We account for differences in household size based on the equivalence scale reported in Fernández-Villaverde and Krueger (2007), Table 1, last column, with a weight of 1 for the first person in the household, 0.34 for the second person and 0.3 for each additional member of the household.

Gross labor income is the sum of wage and salary income. As in Budría Rodríguez et al. (2002), we add a fraction of the business income where this fraction is the average share of labor income in total income in the SCF. *Disposable labor income* is computed using the NBER tax simulator. We use the programs by Kevin Moore provided at http://www.nber.org/~taxsim/ to construct disposable labor earnings for each household in the respective SCF wave. Following the standardized instructions on the NBER website, we feed the following required SCF data into the NBER tax simulator: the U.S. state (we compute the average of the state tax payments across states, since state identifiers are not available in the publicly accessible SCF), marital status, number of dependents, taxpayers above the age of 65 and dependent children in the household, wage income, dividend income, interest and other property income, pensions and gross social security benefits, non-taxable transfer income, rents paid, property tax, other itemized deductions, unemployment benefits, mortgage interest paid and short and long-term capital gains or losses. We then divide the resulting federal and state income tax payments, as well as federal insurance contributions of each household, by the household's gross total income in the SCF. This yields the implicit average tax rate for each household. The mean of that average tax rate for consumers of working age 23-64 in the SCF 2004 is 21.5%. Finally, we use the average tax rate of each household in the respective SCF wave to compute household disposable labor income as (1 - household average tax rate) * household gross labor income (including taxable transfers) and then add non-taxable transfers.

When constructing data counterparts for the wealth and debt portfolio of each household in the model, we refer to Table 1 in the paper.

Housing wealth is defined as the sum of the value of the owner-occupied home that is the primary residence.

Gross secured debt is defined as the sum of mortgage debt, home equity loans and lines of credit secured by the primary residence.

The difference between the value of housing wealth and gross secured debt is the *home equity* held by the household.

Gross financial assets are defined as the sum of assets besides the housing wealth defined above. This is the sum of money in checking accounts, savings accounts, money market accounts, money market mutual funds, call accounts in brokerages, certificates of deposit, bonds, account-type pension plans, thrift accounts, the current value of life insurance, savings bonds, other managed funds, other financial assets, stocks and mutual funds, owned non-financial business assets, residential and non-residential property that is not included in housing wealth, vehicles, jewelry, antiques, and other small durable items.

Gross unsecured debt is defined as all debt besides the gross secured debt defined above. Given that we have to account for the total debt of each household, this balance sheet position also includes auto loans which are secured but not by the primary residence.

The difference between the gross financial assets and gross unsecured debt is the *other equity* held by each household.

Net worth is then defined as the sum of home equity and other equity.

We still need to define the data counterparts for unsecured debt, secured debt and financial assets in the model. These counterparts are not equal to the gross positions, since many households in the data hold debt and financial assets at the same time, which cannot occur in the model. In order match the SCF data to the model, we consolidate the data at the household level so that households indeed hold either debt or financial assets. We proceed in the following way:

Unsecured debt is zero for households with non-negative other equity, and equals other equity if other equity is negative. *Secured debt* for households whose other equity is negative is set equal to their gross secured debt and their *financial assets* are set to zero.

For households who hold positive amounts of other equity, we then consolidate these positions with gross secured debt to obtain the corresponding measures as follows.

Secured debt is zero for households whose sum of gross secured debt and positive amounts of other equity is positive. Otherwise secured debt equals gross secured debt net of positive amounts of other equity.

Financial assets are zero for households whose sum of gross secured debt and positive amounts of other equity is negative. Otherwise financial assets equal positive amounts of other equity net of gross secured debt.

Net financial assets are the sum of *financial assets*, *secured debt* and *unsecured debt*.

It remains to describe how we classify households as bankrupt.

Bankruptcy: We classify a household as bankrupt in the SCF 2004 if the household head or husband/wife/partner have filed for bankruptcy in the last year. We divide by the number of household members who may have declared bankruptcy (the household head and, if applicable, the husband/wife/partner) in order to compute bankruptcy rates per person.

Sample selection criteria: We drop observations if gross labor income is negative or insufficient information is available to compute net labor earnings with the NBER tax simulator (17 observations in the SCF 2004 are deleted), net worth is smaller than -1.2 in terms of the population average of disposable labor income in the respective year (an additional 19 observations of the SCF 2004 are deleted), and unsecured debt is larger than 10 in terms of the sample average of disposable labor income (one additional observation in the SCF 2004 is deleted). These sample selection criteria contain the effect of outliers on the sample means, where some of the outliers seem to be related to entrepreneurial activity in which we are not interested for this paper. The resulting sample size is 4,483. The sample size of prime-age households aged between 26 and 55 is 2,577.

B Calibration of the income process

B.1 Income before retirement

In order to construct a measure for earnings risk before retirement, we recover ϕ_j from the SCF data for consumers aged between 24 and 65, which corresponds to income realizations in the model between the ages of 23 and 64, since households are asked about income in the previous year. We regress the log of earnings on a quartic age polynomial which approximates the age-earnings patterns in the data well (Murphy and Welch, 1990). We then use the standard deviation of the residuals in the regression to calibrate the distribution of earnings shocks z_{ij}. We assume that the shocks are drawn from a log-normal distribution, where in our calibration to the SCF 2004, $z_{2004} \sim \mathcal{N}(0, 0.603)$. Although a formal test rejects log-normality due to some skewness, log-normality is a rather good parametric approximation of the data. The assumption of log-normality is attractive because it is convenient when we approximate the AR(1) income process by a Markov chain.

We calibrate the annual autocorrelation of log-earnings shocks as $\rho = 0.95$, which implies a variance for the innovations ε_{ij} of 0.059. We have checked the robustness of our results for $\rho = 0.97$, which implies a lower variance for the innovations of 0.036. These values for the autocorrelation and the variance of the innovations are within the range of values commonly used in the literature (see, for example, Kopecky and Suen, 2010). We approximate the AR(1) process for z_{ij} in equation (12) of the paper by a Markov chain with 11 income states to contain the computational burden, using the so-called Rouwenhorst method. As pointed out by Kopecky and Suen (2010), this method performs particularly well for highly persistent processes.

Since the SCF surveys are repeated cross-sections and we do not observe the full life-cycle income of most cohorts in the period for which SCF surveys are available, we convert the cross-sectional age-earnings patterns into deterministic life-cycle profiles accounting for growth in life-cycle income. As further explained below, we compute the growth rate of average net labor earnings by constructing a pseudo panel using all comparable SCF waves since 1983. We use that panel to regress log-labor earnings on a quartic age polynomial and a linear time trend. We find that this parsimonious specification explains the data well. Most importantly for our purposes, we find that annual earnings growth is 1%. The estimation results also support our assumption that cohort effects are not important, beyond the linear time trend of earnings, when constructing the life-cycle profiles with cross-sectional data. Statistically we cannot reject the hypothesis at the 1% significance level that the coefficients of cohort dummies are zero in the regression of log-labor earnings on a quartic age polynomial and a linear time trend.

Given these results, we use average labor earnings as the income unit, which grow at an annual rate of 1%. This deterministic growth is taken into account by adjusting the cross-sectional age-earnings patterns with a growth factor of $1.01^{(age-base\ age)}$. The *base age* is the reference age which will allow us to make income units comparable across cohorts in a specific year.

By considering deterministic income growth over the life cycle, we attribute only part of the cross-sectional variation in earnings to idiosyncratic labor income risk. Compared with studies based on other surveys that do not include as many wealth-rich consumers as the SCF, our variance of idiosyncratic income is higher. For example, in our calibration for 2004 the variance of log-earnings is roughly 0.1 above the variance reported in Figure 4 in Krueger and Perri (2006).

B.2 Income after retirement

After retirement, consumers receive individual-specific retirement benefits b_i. These benefits are approximated based on the U.S. social security legislation (see http://www.ssa.gov). Retirement benefits in the U.S. depend on the 35 highest annual earnings before retirement. In terms of the recursive formulation of the model this would imply that, until retirement, the history of labor earnings would enter the model as a state variable. Clearly this would make the numerical solution of the model extremely costly. We thus follow Yang (2009) and determine retirement benefits conditional on the last income before retirement. More precisely, we proceed with the following steps.

First, we transform the net labor earnings y_{ij} of the model into gross labor earnings $\widetilde{y}_{ij}$ using the average tax rate of 0.215 for the sample of households with a head aged between 24 and 65 in the SCF 2004 (including FICA taxes).

Second, we take into account that, for the computation of retirement benefits in the U.S., age-j earnings of individual i are scaled by average earnings growth that has occurred between age j and the last period before retirement $T^r - 1$. We thus multiply gross labor earnings $\widetilde{y}_{ij}$ in periods $j < T^r$ by the factor $1.01^{(T^r-1-j)}$ to obtain indexed gross labor earnings.

Third, we compute the average indexed gross labor earnings $\overline{y}(z_{i,T^r-1})$ over the last 35 years before retirement $[T^r - 35, T^r - 1]$ for a consumer who has a realization of the stochastic component of labor earnings z_{i,T^r-1} and gross earnings $\widetilde{y}_{i,T^r-1}$ in the last year before retirement. Clearly, there are many different histories of earnings which lead to $\widetilde{y}_{i,T^r-1}$. We assign probabilities to these histories using the reverse transition probability $R(z_{ij}, z_{i,j-1})$. This corresponds to the probability that $z_{i,j-1}$ is the predecessor of z_{ij}. Applying Bayes' rule, we can compute this probability as

$$R(z_{ij}, z_{i,j-1}) = f(z_{i,j-1})\frac{P(z_{i,j-1}, z_{ij})}{f(z_{ij})},$$

where P is the standard "forward" transition probability and $f(\cdot)$ is the unconditional probability obtained from the stationary distribution.

Fourth, we set the social-security income cap at \$87,000 and the first and the second bendpoints at \$606 and \$3,653, respectively, as specified in the U.S. social security legislation for 2003 (since labor earnings in the SCF 2004 are recorded for the previous year). We then convert this cap and these bendpoints into model units, dividing by the average equivalized net labor earnings of \$30,866 in the SCF 2004, and adjust them for average earnings growth over the life cycle as specified in the U.S. social security legislation.

Finally, we apply the formula as documented on the website http://www.ssa.gov/OACT/COLA/piaformula.html to compute retirement benefits as

$$b(z_{i,T^r-1}) = \begin{cases} 0.9\ \overline{y} & \text{if } \overline{y} < bp_1 \\ 0.9\ bp_1 + 0.32\ (\overline{y} - bp_1) & \text{if } bp_1 \leq \overline{y} < bp_2 \\ 0.9\ bp_1 + 0.32\ (bp_2 - bp_1) + 0.15\ (\overline{y} - bp_1) & \text{if } bp_1 \leq \overline{y} < cap \\ 0.9\ bp_1 + 0.32\ (bp_2 - bp_1) + 0.15\ (cap - bp_1) & \text{if } \overline{y} \geq cap\ , \end{cases}$$

where $\overline{y} = \overline{y}(z_{i,T^r-1})$ and bp_1 and bp_2 denote the two bendpoints.

Our calibration of retirement benefits implies that the replacement ratio of benefits over gross income is 51% for the median income in the last period before retirement. This replacement rate is similar to the rates reported in Biggs and Springstead (2008).

B.3 Pseudo-panel estimation to compute average earnings growth

The SCF is a triennial survey and comparable data exist for the period from 1983 to 2010. As is common practice, we do not use the 1986 survey, since it was only a limited reinterview

Cohort number	*Age in 1983*	*1983*	*1989*	*1992*	*1995*	*1998*	*2001*	*2004*	*2007*	*2010*
0	0–2	–	–	–	–	–	–	–	131	256
1	3–5	–	–	–	–	–	–	147	147	329
2	6–8	–	–	–	–	–	140	162	173	284
3	9–11	–	–	–	–	171	197	164	188	300
4	12–14	–	–	–	157	175	193	211	210	361
5	15–17	–	–	143	210	193	190	249	242	376
6	18–20	–	91	165	225	209	236	266	287	419
7	21–23	–	117	209	226	261	296	296	261	444
8	24–26	237	133	249	257	286	330	306	338	450
9	27–29	277	204	237	270	290	347	334	306	444
10	30–33	251	176	241	290	275	323	340	313	447
11	34–36	262	208	249	310	297	269	303	277	357
12	37–39	232	219	255	249	299	292	291	270	323
13	40–42	238	185	218	269	234	235	279	241	–
14	43–45	214	177	225	188	218	192	181	–	–
15	46–48	205	171	186	199	178	175	–	–	–
16	48–50	196	180	154	203	168	–	–	–	–
17	51–53	211	165	185	189	–	–	–	–	–
18	54–56	198	165	206	–	–	–	–	–	–
19	57–59	197	162	–	–	–	–	–	–	–
Sums		2,718	2,353	2,922	3,242	3,254	3,415	3,529	3,384	4,790

Table 1: Number of households in each earnings cohort per year. Source: Authors' calculations based on the SCF.

survey with respondents to the 1983 SCF. This leaves us with nine repeated cross-sectional surveys in 1983, 1989, 1992, 1995, 1998, 2001, 2004, 2007 and 2010.

We construct a pseudo panel for three-year age cohorts, computing cohort averages for log-labor earnings and the terms of the quartic age polynomial. Table 1 displays the number of observations for each of the cohort-year cells in the unbalanced pseudo panel for working-age households with a head aged between 24 and 65. Recall that this corresponds to earnings between the model ages of 23 and 64, since households in the SCF are asked about their earnings in the previous year. Cell averages are computed with at least 90 observations and with well above 100 observations for most cohort-year cells. See the seminal paper by Browning, Deaton and Irish (1985) for further background on pseudo panels.

We augment the income process before retirement, presented in the calibration section, with a linear time trend to capture time effects and use the pseudo panel to estimate the log-linear specification. Note that this specification derives from the structural assumptions about the income process. Whereas the log-linear regression of labor earnings thus has a structural interpretation, a similar regression with wealth as dependent variable does not. In fact, such a regression would be misspecified for our model. Note that we want to calibrate our model to the most recent data in the 2000s. Hence, we use the pseudo-panel regressions only to compute the annual growth rate of earnings. We then use this growth rate to map between the age cross-sections in the last available SCF survey before the financial crisis (from 2004) and the life-cycle profiles of labor earnings and wealth in the model.

Table 2 displays the results of the regressions. In our preferred specification in column (1), we estimate an annual growth rate of labor earnings of approximately 1%. In column (2) we replace the linear time trend with time dummies. Comparing the adjusted R^2 statistic in columns (1) and (2) reveals that the fit of the data remains good with the more parsimonious specification in column (1). As is well known, column (3) shows that the data variation could also be explained with cohort dummies. Because of linear dependence, we cannot simultaneously use age, year and cohort dummies as regressors. If we restrict the age effects to a quartic polynomial and the time effect to a linear trend, as in the specification in column (1), we cannot reject the hypothesis at a 1% significance level that the coefficients of cohort dummies are jointly zero when cohort dummies are added to that specification. The test statistic is $F(18, 97) = 1.93$ with a p-value of 0.022. The lack of strong significance gives some support to the assumption in the paper that cohort effects are captured with the linear time trend.

C Life-cycle profiles

Figure 1 displays the life-cycle profiles for variables of interest where we take averages over the simulated population of 100,000 consumers aged between 26 and 76. Home equity, financial assets and unsecured debt are in units of average net-labor earnings per adult-equivalent. Figure 1 shows that financial assets and home equity display the familiar tent shape over the life cycle. The home ownership rate steadily increases over the life cycle before consumers sell their owned housing wealth at the end of life. Unsecured debt is largest (in absolute terms) for young consumers and then decreases with age. As expected, consumers substantially reduce their home equity and financial assets during retirement. Home equity,

Regressors	*Dependent variable: log-labor earnings* (1)	(2)	(3)
age	0.495 (0.201)*	0.508 (0.189)**	0.552 (0.188)**
age^2	-0.017 (0.007)*	-0.017 (0.007)*	-0.019 (0.007)**
age^3	0.00027(0.00011)*	0.00028(0.00010)**	0.00029(0.00010)**
age^4	$-1.6/10^6$ $(6.1/10^7)$**	$-1.6/10^6$ $(5.8/10^7)$**	$-1.7/10^6$ $(5.8/10^7)$**
linear time trend	0.008 (0.001)**	–	–
constant	4.32 (2.05)*	4.16 (1.93)*	3.82 (1.92)*
time dummies	No	Yes**	No
cohort dummies	No	No	Yes**
Adj. R^2	0.799	0.822	0.826
Observations	121	121	121

Table 2: Regressions for log-labor earnings of cohorts between the ages of 23 and 64. Notes: Standard errors in brackets. **: 1% significance level, *: 5% significance level. Source: Authors' calculations based on the SCF.

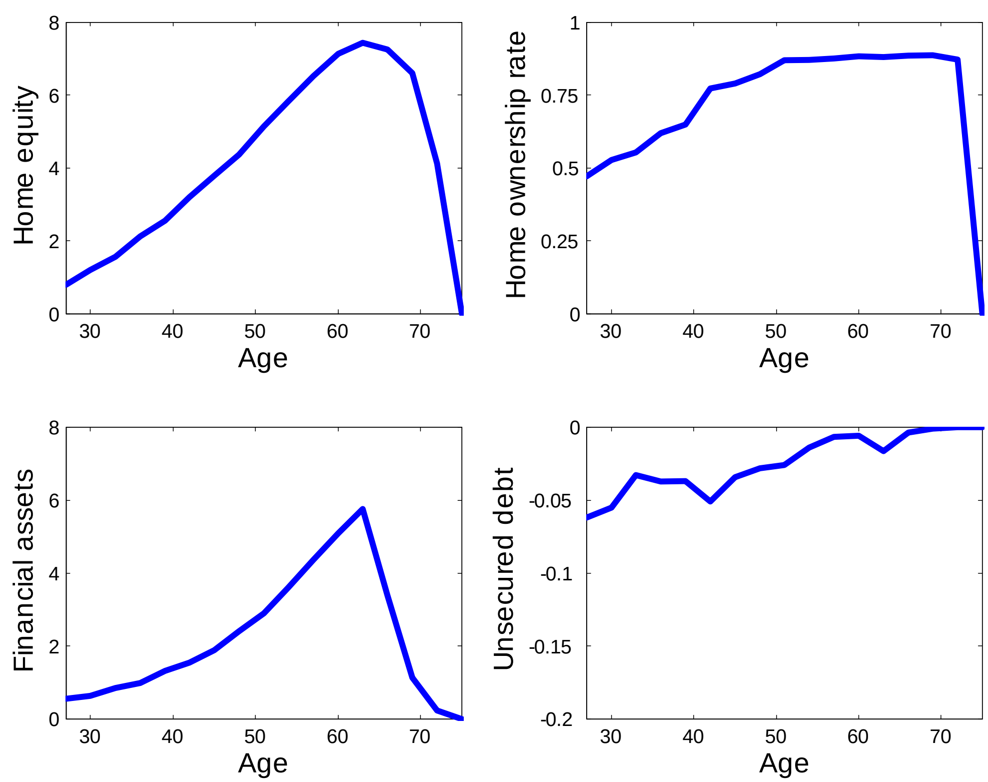

Figure 1: Average life-cycle profiles predicted by the model. Source: Authors' calculations based on the model. Note: The unit is the average of net labor earnings.

Parameters			
		$\mu = 0.9$	$\mu = 0.975$
Preferences	β	0.9675	0.9675
	θ	0.76	0.76
	σ	1.82	1.82
	φ^r	0.935	0.9425
	ψ	0.045	0.045
Technology	δ	0.02	0.02
	c_f^+, c_f^-	0.025	0.025
	μ	0.9	0.975
	$h^\dagger$	1.2	1.2
Interest rates	r^a	0.04	0.04
	r^s	0.05	0.05
	$\underline{r^u}$	0.051	0.051

Table 3: Parameters for the calibrated numerical solution with $\mu = 0.9$ or $\mu = 0.975$. Notes: Annualized parameters.

that is housing wealth net of secured debt, drops by a large amount in the penultimate period when much of the financial assets have been depleted already.

The decumulation of wealth components towards the end of the retirement period clearly results from the assumption of a finite life, as in Livshits et al. (2007). Allowing for a positive probability of death and assuming accidental bequests, however, would substantially increase the computational burden of our model, since it requires consistency of bequests with accumulation behavior, both of which need to be determined simultaneously in equilibrium.

The properties of the model solution in earlier periods of life, which are relevant for our comparisons of the model with the data, are largely independent of any specific assumptions about the behavior in the terminal period. This is due to the convergence properties of backward induction of value functions employed in our analysis.

D Robustness: higher loan-to-value ratio

In this section we present robustness results if we allow for higher loan-to-value ratios of 0.9 or 0.975 instead of 0.8 as in the benchmark. Table 3 shows that only small changes in the parameter values are needed to recalibrate the model for the higher loan-to-value ratios.

Figures 2 and 3 show that the predicted age profiles (solid lines) continue to fit the data

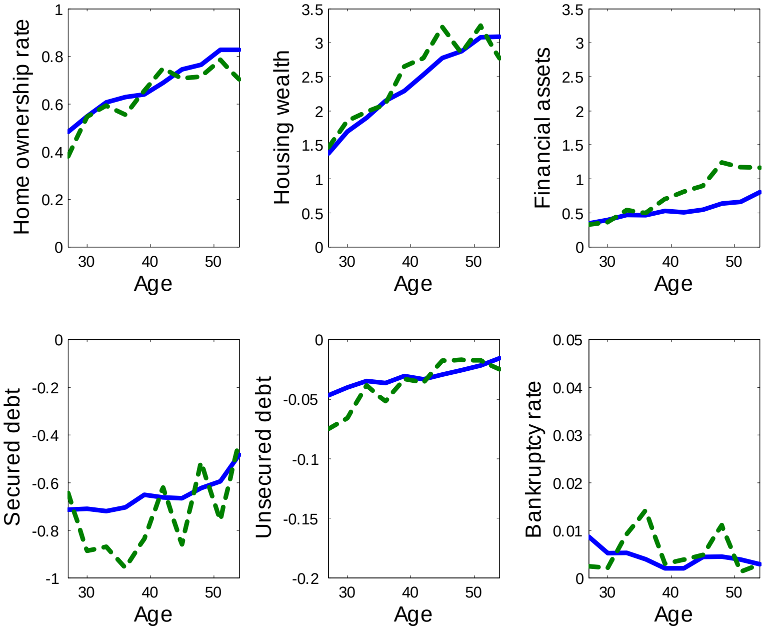

Figure 2: Loan-to-value ratio $\mu = 0.9$: cross-sectional age profiles predicted by the model (solid lines) and the data (dashed lines) for prime-age consumers aged 26–55 up to the 90th percentile of the net worth distribution. Source: Authors' calculations based on the model and the Survey of Consumer Finances (SCF) 2004. Notes: The unit is the average of annual net labor earnings. The bankruptcy incidence in the data is multiplied by 2/3 for the fraction of job-related bankruptcies and by 0.7 for the fraction of bankruptcies under Chapter 7.

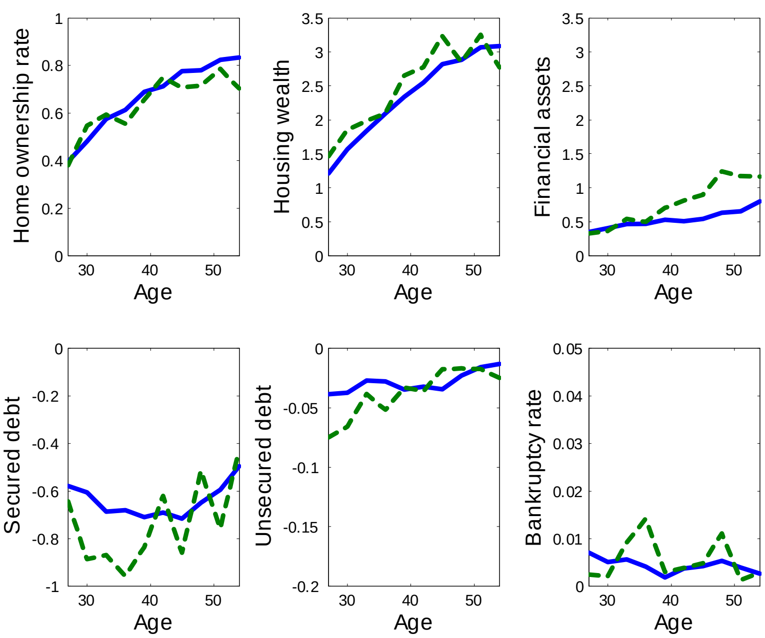

Figure 3: Loan-to-value ratio $\mu = 0.975$: cross-sectional age profiles predicted by the model (solid lines) and the data (dashed lines) for prime-age consumers aged 26–55 up to the 90th percentile of the net worth distribution. Source and notes: see previous figure.

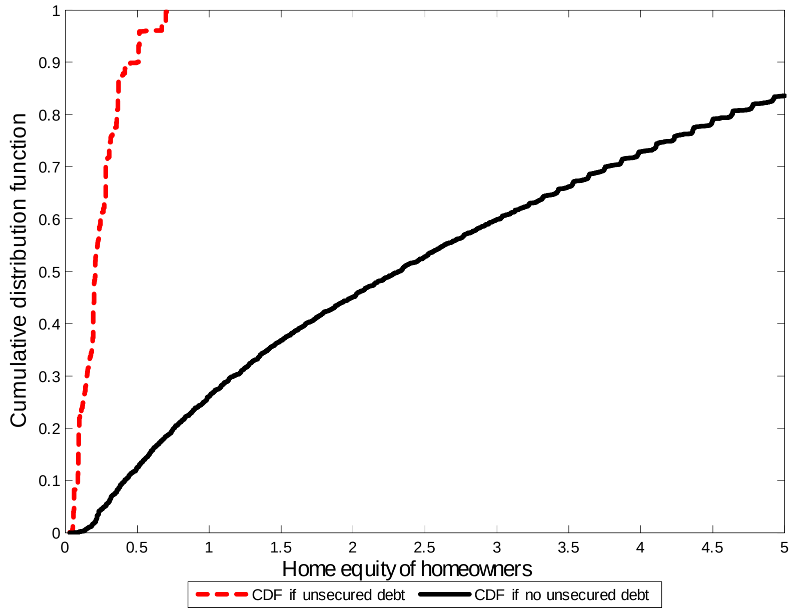

Figure 4: Loan-to-value ratio $\mu = 0.9$ and model predictions for the cumulative distribution function of home equity for prime-age homeowners with and without unsecured debt. Source: Authors' calculations based on the model. Notes: The functions are plotted for home equity in the interval $[0; 5]$.

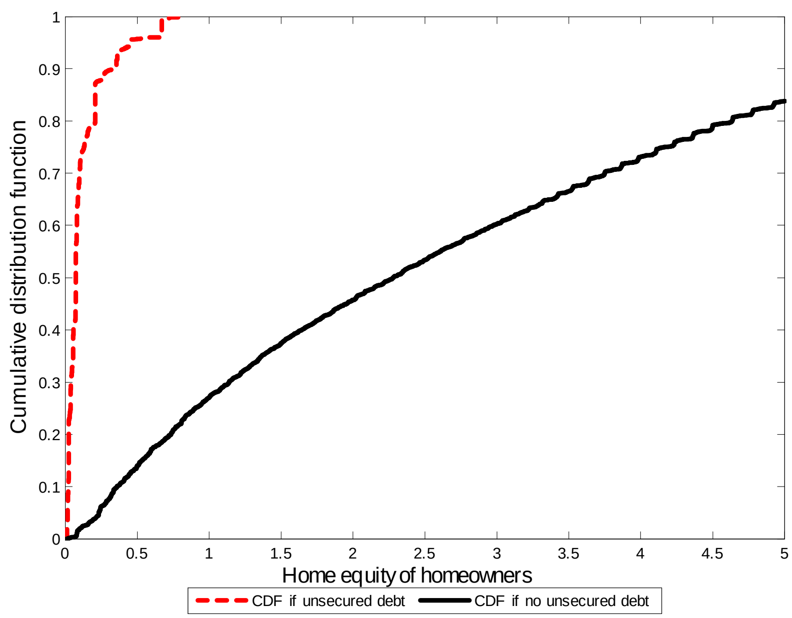

Figure 5: Loan-to-value ratio $\mu = 0.975$ and model predictions for the cumulative distribution function of home equity for prime-age homeowners with and without unsecured debt. Source and notes: see previous figure.

(dashed lines) rather well for both cases. We have explained in the main text that the home-equity distribution for homeowners with unsecured debt is important for the quantitative effects of homestead exemptions on the model equilibrium. Figures 4 and 5 display the home equity distribution for homeowners with unsecured debt if we increase the loan-to-value ratio from 0.8 to 0.9 or 0.975, respectively. Comparison with Figure 5 in the paper shows that homeowners with unsecured debt hold less home equity as the restriction on the maximal loan-to-value ratio is relaxed from 0.8 to higher values of 0.9 or 0.975. For the calibrated parameters, they find it optimal to reduce their home equity before borrowing unsecured. Less home equity of homeowners with unsecured debt implies that even smaller exemptions than in the benchmark case eliminate the value of home equity as informal collateral and a commitment device.

As shown in Tables 4 and 5, a higher loan-to-value ratio strengthens our quantitative result on the small effects of homestead exemptions on the price and quantity of unsecured debt in the model equilibrium. Compared to the benchmark case with a lower loan-to-value ratio $\mu = 0.8$, the welfare effect of homestead exemptions under the veil of ignorance is qualitatively similar but quantitatively smaller. If the homestead exemption is eliminated, the welfare of consumers under the veil of ignorance increases by 0.12% in consumption-basket equivalents if $\mu = 0.9$ and by 0.08% if $\mu = 0.975$ (instead of 0.3% in the benchmark case with $\mu = 0.8$). The intuition is that the benefit of cheaper unsecured debt is smaller for homeowners because, with higher regulated maximum loan-to-value ratios, they can obtain more secured debt and hold less home equity. The welfare effect of a homestead exemption could become positive if regulation allowed loan-to-value ratios to exceed the value of the collateral net of adjustment costs in the model. This would require to extend the model introducing default on mortgages and foreclosures. In such a model, more generous homestead exemptions in bankruptcy procedures for unsecured debt could help some households to avoid foreclosures. See Berkowitz and Hynes (1999), Li, White and Zhu (2010), Mitman (2012) and Morgan, Iversen and Botsch (2012) for further discussion.

	(1)	(2)	(3)	(4)	(5)
Variable / Exemption level $h^\dagger =$	0	0.24	0.49	0.81	1.2
Unsecured debt (in av. earnings)	-0.04	-0.03	-0.03	-0.03	-0.03
Risk premium on unsec. debt (in %-points)	1.3	1.8	1.8	1.8	1.8
Job-related bankruptcy (in %)	0.39	0.42	0.42	0.42	0.42
Incidence of unsecured debt (in %)	20.8	19.2	19.3	19.6	19.5
Home ownership rate (in %)	72.8	67.5	67.6	67.6	67.6
Both types of debt (in %)	10.8	5.2	5.4	5.6	5.5
Conditional means					
Unsecured debt (in av. earnings)	-0.22	-0.16	-0.19	-0.18	-0.18
Risk premium on unsec. debt (in %-points)	1.0	0.7	0.8	0.8	0.8
Only unsecured debt (in %)	10.0	14.0	13.9	14.0	14.0
Conditional means					
Unsecured debt (in av. earnings)	-0.16	-0.16	-0.16	-0.16	-0.16
Risk premium on unsec. debt (in %-points)	1.5	2.2	2.2	2.2	2.2

Table 4: Loan-to-value ratio $\mu = 0.9$: equilibrium effects of changes in homestead exemptions. Source: Authors' calculations based on the model. Notes: The unit is the average of annual net labor earnings.

	(1)	(2)	(3)	(4)	(5)
Variable / Exemption level $h^\dagger =$	0	0.24	0.49	0.81	1.2
Unsecured debt (in av. earnings)	-0.03	-0.03	-0.03	-0.03	-0.03
Risk premium on unsec. debt (in %-points)	1.7	2.2	2.2	2.1	2.2
Job-related bankruptcy (in %)	0.38	0.43	0.43	0.43	0.43
Incidence of unsecured debt (in %)	17.1	17.0	17.2	17.3	17.3
Home ownership rate (in %)	67.2	67.1	67.0	67.0	67.0
Both types of debt (in %)	4.5	4.3	4.5	4.6	4.6
Conditional means					
Unsecured debt (in av. earnings)	-0.19	-0.20	-0.19	-0.20	-0.20
Risk premium on unsec. debt (in %-points)	1.6	2.3	2.3	2.3	2.2
Only unsecured debt (in %)	12.6	12.8	12.8	12.7	12.7
Conditional means					
Unsecured debt (in av. earnings)	-0.16	-0.16	-0.16	-0.16	-0.16
Risk premium on unsec. debt (in %-points)	1.7	2.1	2.1	2.1	2.1

Table 5: Loan-to-value ratio $\mu = 0.975$: equilibrium effects of changes in homestead exemptions. Source and notes: see previous table.

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