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Savings, Portfolio Choice, and Retirement Expectations

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Abstract

Studying household investment behavior is essential for understanding the full consequences of old age social security benefits. Using data from six waves of the Health and Retirement Study, we analyze the dynamics of portfolio composition before respondents start claiming social security benefits. We consider ownership as well as amounts held of several types of assets and debts. Using panel data censored regression models, portfolio adjustment is explained on the basis of demographics like gender, race, and year of birth, education level, household income, and perceived social security entitlements. We find that expectations of old age social security benefits have little effect on portfolio decisions, although there is some evidence that higher expected social security benefits lead to more risky financial investments, particularly in IRAs.

1. Introduction

To understand the consequences of social security provisions after retirement, it is essential to know how people prepare for retirement by saving and by allocating their savings across different types of assets, such as saving accounts, stocks and bonds, individual retirement accounts, life insurances, and housing. Similarly, it matters how people manage their mortgage and consumer debt. Savings and portfolio choice decisions determine the amount of wealth that people hold at retirement and the need for additional social security provisions. Moreover, (dis)saving and portfolio choices after retirement determine how such needs develop in the years after retirement. While many studies have analyzed portfolio composition at a given point in time,[1] much less work has been done on the dynamics of portfolio adjustment in general, and in the years around retirement in particular. Yet, individuals need to adjust their portfolio in the face of changing circumstances, e.g. changes in job prospects, changes in health, or changes in expected social security and pension entitlements. The available panel data in the Health and Retirement Study (HRS), following the United States birth cohort 1931-1941 over the period 1992-2002, together with recent progress in estimation techniques for panel data models offer new opportunities for such an analysis.

This paper aims at analyzing how households adjust the structure of their asset and debt portfolios in the years around retirement. What do portfolios of the HRS cohort look like shortly before and after retirement? Who are the people who invest in risk free assets such as saving accounts or in risky assets such as shares of stock, stock mutual funds, or Individual Retirement Accounts? Do respondents typically hold certain combinations of assets, or do they typically specialize in one or two asset types? Which factors drive savings and portfolio choices? How do people adjust to changes in these factors and how quick is the adjustment? In particular, and very relevant for policy, does investment behavior vary with perceived social security entitlements?

The HRS contains rich longitudinal information on elderly Americans, including information on ownership and amounts held of a number of asset

[1] The volume by Guiso, Haliassos and Jappelli (2002) contains studies of household portfolio choice for various countries and for special groups. One of these groups is the elderly, studied in the chapter by Michael Hurd (Hurd 2002). Another recent study on portfolio choice using the HRS is Rosen and Wu (2004). Recent examples of portfolio analyses for the US in general are King and Leape (1998), Poterba and Samwick (2002), and Flavin and Yamashita (2002).

categories. This is the ideal data source for the current project. The HRS also contains a rich set of background variables on family composition, health, employment and employment history, and future expectations on old age social security income, which may serve as explanatory variables. We use the six waves of 1992, 1994, 1996, 1998, 2000, and 2002. This period includes the stock market boom and bust, which will be of particular importance for understanding household investment behavior.

In this paper we use static random effects panel data censored regression models for each type of assets and debts that we consider. The censored regression model is used to account for the fact that many types of assets are held by a limited fraction of households only. We account for unobserved heterogeneity that leads to correlation between amounts held in a certain type of assets or debts by a given household in different time periods. We focus on the group of households who are not yet claiming social security benefits, and our main research question is how the portfolio decisions of these households are affected by their perceived social security entitlements. These perceived entitlements are self-reported by the household's financial respondents. Although, in principle, actual social security entitlements can be retrieved from restricted data files that can be linked to the HRS data, it is self-perceived social security expectations that play a role for investment behavior according to economic theory.

Theoretical predictions are twofold. First, households with large social security entitlements need less saving for retirement. Therefore, keeping everything else constant, we would expect a negative correlation between expected social security entitlements and amounts invested in most types of assets. Second, social security benefits are a relatively safe source of retirement income for most households, implying that those with high social security benefit expectations should hold more risky portfolios of financial and non-financial assets, keeping constant everything else. The keeping everything else constant (*ceteris paribus*) condition is particularly relevant in this case – high expected social security benefits may also proxy high lifetime resources and past earnings, implying more potential for accumulating wealth in the past. Since labor market history is not observed, this would lead to an omitted variable bias. In our panel data framework, this can be avoided by allowing for household specific effects that are correlated with the permanent component of expected social security benefits. For similar reasons, portfolio choices may not only depend on actual income in a given period, but may

also be associated with permanent income levels, proxied by the average income over the period considered.

In our panel data models, we therefore explain amounts held in types of assets of debts from social security expectations, controlling for socio-economic indicators such as education level, current income, and average "permanent" income, but also controlling for the permanent component of expected entitlements, proxied by the sample average of perceived entitlements in the time periods the household is observed. The main finding is that there is a positive raw correlation between perceived social security entitlements and amounts invested in many asset types, which largely disappears once other factors but mainly average perceived entitlements are controlled for. Thus the panel data models lead to very different conclusions than simple cross-section models. The only effect that remains is a positive effect of social security entitlements on risky financial assets, particularly IRAs. This confirms the second theoretical prediction – these with a large perceived buffer in the sense of expecting high social security benefits, are typically the ones who invest their private savings in more risky assets. We find essentially no evidence for the first theoretical prediction.

The remainder of this paper is organized as follows. Section 2 describes the asset data in the HRS and the trends in ownership and amounts held. Section 3 presents the results of some censored regression models. Section 4 concludes.

2. Data

We use data from the first six waves of HRS, a biennial household survey that started in 1992. We only consider the original HRS cohort randomly selected in 1992, consisting of households with at least one spouse born between 1931 and 1941. This cohort was between 51 and 61 years of age at the time of the first interview, and between 61 and 71 years of age in 2002, the last interview in our data set. Thus many HRS respondents have retired during the observation window, making this an appropriate age group for studying decisions related to planned and realized retirement.

Table 1 lists the asset and debt categories that we consider and their ownership rates.[2]

[2] For convenience, we also talk about "ownership" in case a household has a certain type of debt.

Table 1. Asset and Debt Holdings HRS 1992-2002

Assets	Ownership rates (%)					
	1992	1994	1996	1998	2000	2002
Checking & Saving	84.5	85.6	87.0	85.6	86.9	88.0
Bonds	7.3	6.9	8.8	8.2	8.0	8.5
Stocks	32.3	35.4	36.0	34.5	36.2	35.3
IRAs, Keoghs	44.6	47.7	47.2	39.6	41.7	39.3
CDs, SVbonds, T-bills	28.2	24.8	23.7	25.0	26.6	25.6
Business assets	19.2	18.2	15.0	11.2	11.2	10.4
Primary residence	82.1	83.1	78.5	81.5	82.2	82.3
Other real estate	26.4	27.2	26.7	19.6	19.2	17.3
Transportation	92.6	92.5	92.2	86.6	87.5	86.5
Other assets	17.5	25.6	20.8	15.6	16.3	14.5
Debts	Holding rates (%)					
Mortgage	46.6	41.9	36.8	31.7	32.5	31.4
Other home loans	11.6	10.9	11.2	8.3	8.2	8.7
Other debt	39.1	36.8	34.2	28.3	29.7	26.0
Net housing wealth	83.6	81.8	77.3	82.2	83.0	82.8
Nonhousing fin. wealth	88.8	86.7	89.5	88.9	89.6	91.2

Notes:
All rates weighted with household level sample weights.
Checking & Saving: checking or saving accounts or money market funds;
Bonds: corporate, municipal, government or foreign bonds, or bond funds;
Stocks: shares of stock or stock mutual funds;
CDs: CDs, government savings bonds, or treasury bills;
Other assets: other savings or assets, such as jewelry, money owed by others, a collection for investment purposes, rights in a trust or estate or an annuity not yet mentioned;
Transportation: any durable meant for transportation, like cars, trucks, a trailer, a motor home, a boat or an airplane;
Net housing wealth: Primary residence + other real estate - mortgage - other home loans

The most commonly held assets are checking and saving accounts and primary residence. The fraction of households having any checking or savings account appears to be increasing. Since we are following one cohort over time, this can be a pure time trend or an age effect. The former seems more plausible. Individual Retirement Account type assets (IRAs and Keoghs) show a decreasing trend, indicating that more IRAs get cashed than money is put into them. In this age group that is to be expected. Similarly, the trend in business assets is strongly negative as one would expect for this age group, where people are more often selling than buying their businesses. There is no trend at all in the ownership rate of the primary residence. On

the other hand, the ownership rate of real estate other than the primary residence is clearly falling over time. Again, the most plausible explanation seems an age effect – the older people get, the less they want to invest in real estate property, possibly due to the labor intensive nature of this type of investment. The falling fractions of people holding debts, either mortgages, other home loans, or other types of debt, suggest that many households use their IRAs or business assets to repay their debts.

In each wave, more than 80% of all households have some housing assets, and there is not much of a trend there. The fraction with at least one type of financial assets is increasing over time, which is probably explained by the increasing ownership of checking and saving accounts.

Table 2 presents the median amounts of the types of assets and debts that we consider (not corrected for inflation). It shows the well-known fact that the financial assets with the highest ownership rates are not always the most important assets in terms of the amount held. Stocks are held by about one third of all households, but the median amount in the most recent waves is more than five times higher than that of checking and saving accounts, implying that the aggregate value of stocks held is larger than that of checking and saving accounts held. There is a clear positive time trend in the median amounts of stocks and IRAs and Keoghs until 2000; this seems to have come to a halt with the stock market downturn. Still, the same pattern is present in CDs, Saving Bonds and T-bills. The value of business assets is increasing substantially over time. Apparently, as revealed by Table 1, many households are selling their business assets in the time period considered, but those who keep them are typically the ones who have most of them.

The increasing trends in the median values of the primary residence and other real estate may reflect rising housing prices over the period considered. The rising mortgage amounts probably are due to a selection effect – households with a larger mortgage are less likely to pay off their mortgage debt. The median values of net housing wealth as well as financial wealth are also increasing. Whether this is in line with life-cycle theory is hard to say – even in the later waves, many respondents have not yet retired, so it not clear whether dissaving after retirement should dominate these aggregate figures.

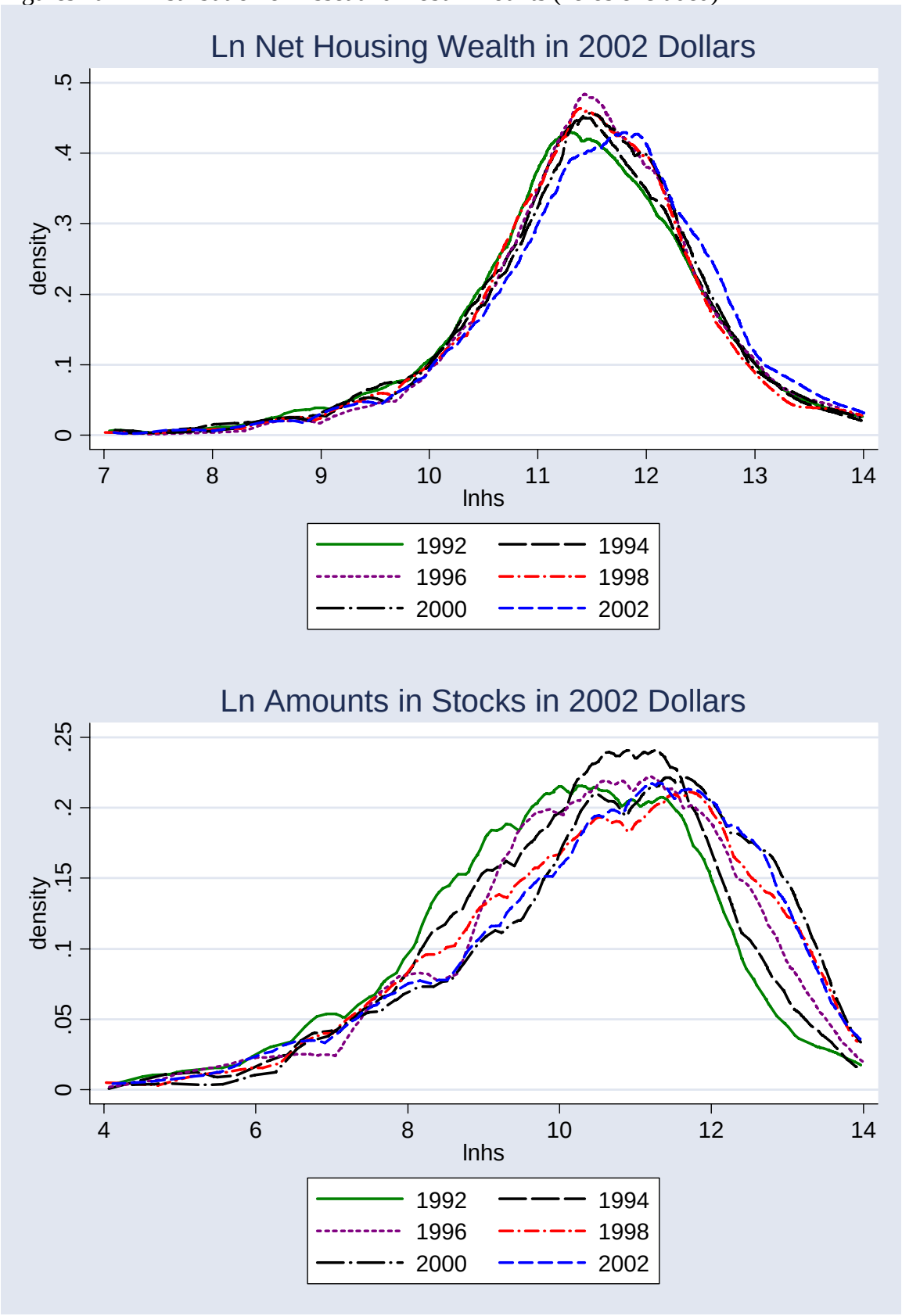
Table 2. Asset and Debt Holdings HRS 1992-2002

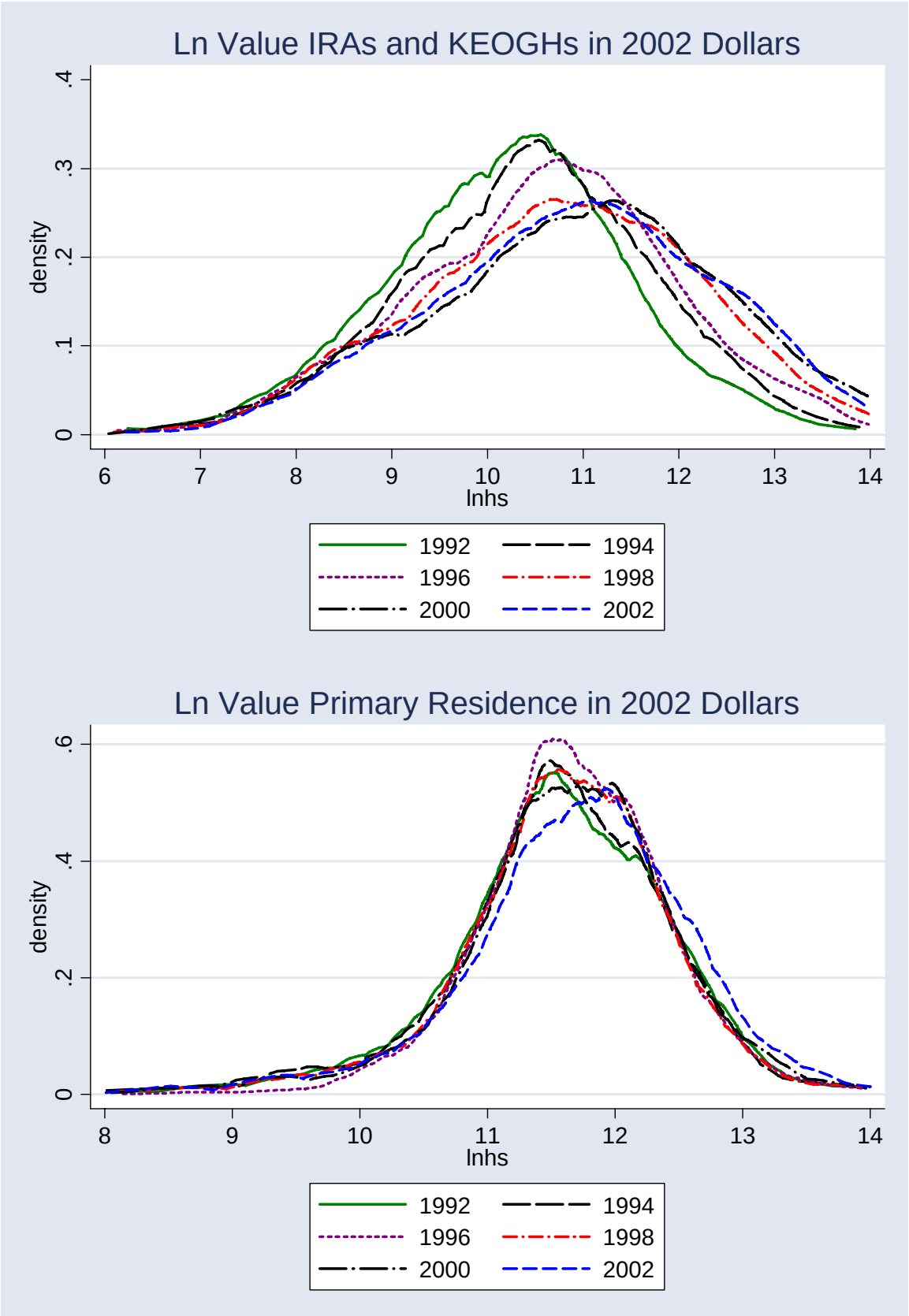
Assets	Median Amount (Amounts ≤ 0 excluded; x $1000)					
	1992	1994	1996	1998	2000	2002
Checking & Saving	5.5	8	8	6	6.4	8
Bonds	12	30	25	25	25	30
Stocks	20	30	36	45	50	50
IRAs, Keoghs	24	30	35	41	52	50
CD-s, SVbonds, T-bills	9	12	17	15	20	20
Business assets	75	90	100	100	135	160
Primary residence	87	85	95	100	110	126.5
Other real estate	50	60	64	70	73	80
Transportation	10	9	10	10	10	11
Other assets	20	12	15	18	20	20
Debts						
Mortgage	30	32	40	46.9	55	60
Other home loans	15	14	14	16	16	20
Other debt	3	3	3	4	4	5
Net housing wealth	75	80	90	85	95	110
Nonhousing financial wealth	20	24.6	30	28.5	33.3	35

Note: all numbers weighted with household level sample weights provided by HRS.

Figures 1a-1f show the development over time in the distribution of the log asset and debt amounts (positive values only) in real terms for selected asset types. For net housing wealth and the real value of the primary residence, not much has changed over time in the shape of the distribution, but the amounts in 2002 are typically higher than in the other years. More seems to be going on with stocks and IRAs and Keoghs. Here there is much more variation over time, in the shape of the distribution but in particular in its location. During the first half of the time period covered by the data, the amounts are growing substantially. This is in line with the booming stock market – IRAs are partly invested in stocks. The distribution of debts seems to be stable and close to log normal. Debts are relatively low in wave 1, but stabilize thereafter.

Figures 1a-1f Distirbution of Asset and Debt Amounts (zeros excluded)




Ln Value IRAs and KEOGHs in 2002 Dollars
density
0
.1
.2
.3
.4
6
7
8
9
10
11
12
13
14
lnhs
1992
1994
1996
1998
2000
2002
Ln Value Primary Residence in 2002 Dollars
density
0
.2
.4
.6
8
9
10
11
12
13
14
lnhs
1992
1994
1996
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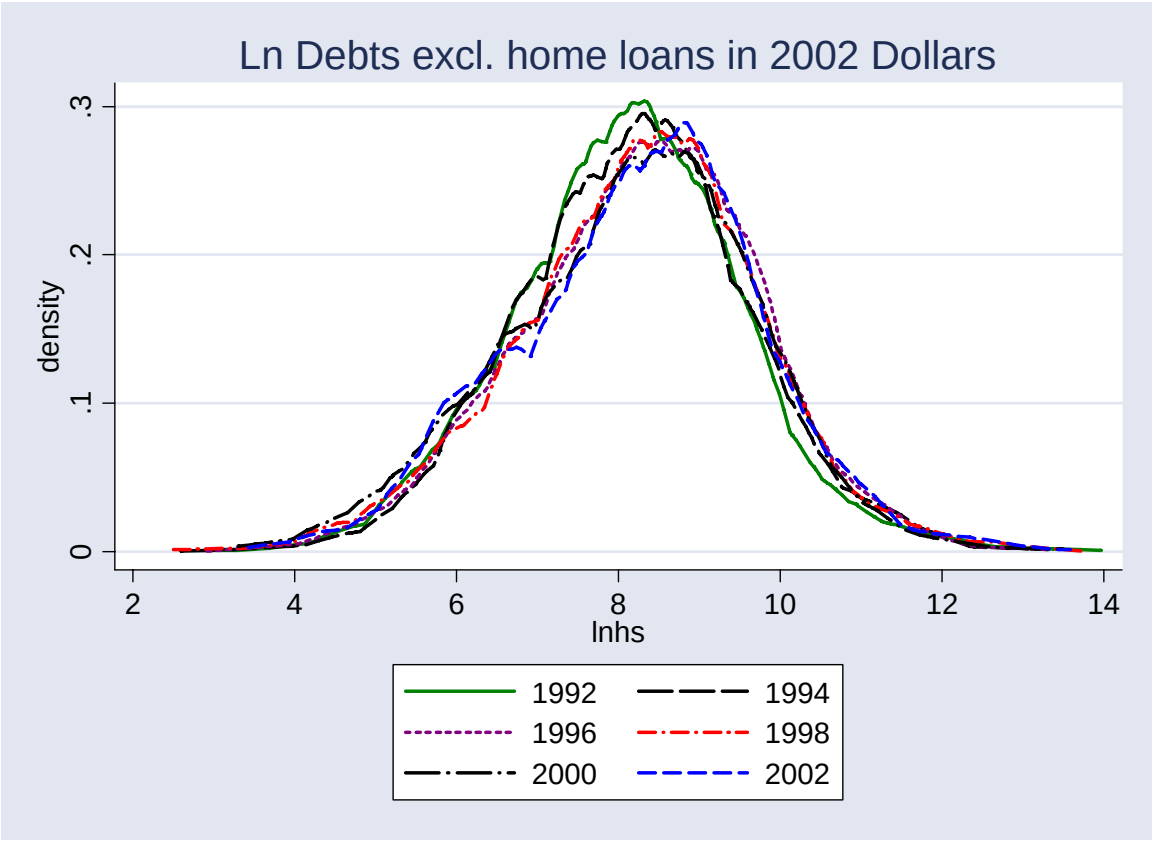
2000
2002



The descriptive statistics presented above refer to all households in the sample, working and not working, claiming social security benefits or not claiming social security benefits. In our analysis using censored regression models, we will focus on the effect of expected future social security benefits on portfolio composition, and will therefore only select households in which the financial respondent and spouse are not yet claiming social security benefits. Moreover, we only select the households for which neither the respondent's expected amount nor the spouse's expected amount is missing. Since the 1992 wave has an unusually large number of observations with missing information on expected social security benefits, and remaining observations are clearly a selective group with expected amounts that are unusually high, we restrict the analysis to the waves 1994, 1996, 1998, 2000 and 2002.

Table 3 presents the number of observations with complete information for each wave, and the descriptive statistics for the main explanatory variable of interest, the expected amount of social security benefits. The number of observations tends to fall over time, because this group of households is reaching an age at which they start claiming, particularly as of 1996. For those who do not yet claim, response rates actually tend to increase over time (Rohwedder and Kleinjans, 2004). The

distributions (corrected for inflation) are quite stable over time. For example, the median varies between 12,383 and 12,950, but the tails also seem quite stable.

Table 3. Distribution of Expected Social Security Benefits

	1994	1996	1998	2000	2002
Observations	2576	2827	2235	1778	1441
Mean	14,555	14,009	14,580	15,008	14,696
1st Quartile	7,283	8,255	7,947	8,776	8,400
Median	12,950	12,383	12,582	12,537	12,528
3rd Quartile	19,665	19,263	19,866	20,059	19,164

Notes:

Expected amount of social security benefits per year, household level, in 2002 US dollars. Observations with missing values excluded.

The complete set of explanatory variables used in the censored regression models is presented in Table 3. The unit of observation is the household, and the information on assets, debts, household income and other financial matters is provided by the financial respondent in the household (the most knowledgeable household member in financial matters). Many of the explanatory variables are individual characteristics of this household member. The first two columns refer to the sample used for estimation, only including those who do not yet collect Social Security benefits and reported their expected future benefits, as explained above. The third column does not impose this selection criterion.

In 1994, the cohort is still relatively young, and not many households have started claiming yet. This is quite different in 2002, where, as expected, those who do not yet claim are predominantly the younger half of the cohort. The majority of households are couples. This fraction falls over time due to death of one spouse in the sample as a whole, but because of selecting the younger groups, the fraction of couples actually increases in the estimation sample.

Table 4. Explanatory Variables (Means and standard deviations)

	Estimation Sample		All	
Variable	1994	2002	2002	Variable description
Ybrth	36.60	40.51	36.75	Year of birth – 1900
	(4.78)	(3.95)	(4.93)	
Married	0.727	0.790	0.627	Dummy Married
Female	0.416	0.416	0.491	Dummy female
Edlow	0.189	0.125	0.225	Dummy education < 12 years
Ed12	0.353	0.340	0.348	Dummy educ. 12 years (benchmark)
Ed1215	0.223	0.253	0.195	Dummy 12<education≤15 years
Edhigh	0.235	0.282	0.232	Dummy education > 15 years
Hispanic	0.041	0.048	0.067	Dummy Hispanic
Nonwhite	0.096	0.095	0.133	Dummy Nonwhite
Ln_income	10.409	10.810	10.373	Log annual household income
	(1.544)	(1.487)	(1.375)	
Working	0.715	0.668	0.405	Dummy working for pay
Ln_exp_SS	9.392	9.392		Log expected Social Sec. benefits
	(0.650)	(0.738)		
Ln_av_inc	10.652	11.010	10.557	Log average household income
	(0.892)	(0.767)	(0.912)	
Ln_av_eSS	9.378	9.559	9.342	Log average Social sec. benefits
	(0.574)	(0.629)	(0.716)	

Notes: All numbers weighted with HRS household level sample weights.

Table presents mean values in the first and last wave and standard deviations in parentheses for non-categorical variables.

Individual characteristics refer to the financial respondent (who answers all questions on household income, assets, and debts). Sample selection: financial respondent 50 years or older. Columns 1 and 2: not claiming OASI benefits and reporting expected OASI benefits. Column 3: all financial respondents age 50 or older.

Ln_income: RAND HRS imputations used in case of missing values.

Ln_exp_SS: financial respondent and spouse; 0 for those do not expect to receive it at any time in the future.

Ln_av_inc: log of average household income over the time periods the household is in the sample.

Ln_av_eSS: log of average expected OASI benefits over the time periods the household is in the sample.

In couples, the majority of the financial respondents are males, but because the singles are mainly widows, almost half of the financial respondents in the total 2002 sample are female. There are four educational groups and their relative size in the total sample remains rather stable over time. The lower educated, however, have a larger tendency to start claiming early, so that their number is relatively low in the sample of those who do not yet claim. They also have a larger tendency not to report

their expected social security benefits. This also applies to nonwhite and Hispanic respondents.

While average income for the estimation sample has increased over time, it should be noted that the estimation sample over represents the higher income groups. This again corresponds to the finding that the higher socio-economic status groups start claiming benefits later and more often report an expected amount. The same arguments can be used to explain why those who report an expected benefits amount in 2002 are typically the households with, on average over the time periods, high expectations.

3. Model

To explain the choice whether to invest in a certain asset type or not, as well as the amounts invested in the chosen types of assets, we use Tobit models for panel data. For asset (or debt) type *j*, household *i* and panel wave *t*, y_{it}^{j} is zero if the asset type is not held, and the log of the amount held if the asset type is included in the household's portfolio. The model explaining y_{it}^{j} is as follows:

$$y_{it}^{j} = \max(0, y_{it}^{j}*)$$
$$y_{it}^{j}* = x_{it}^{'}\beta + \alpha_{i}^{j} + \varepsilon_{it}^{j}$$

Here $y_{it}^{j}*$ is an unobserved latent variable, which can be interpreted as the desired amount held. Due to a nonnegativity constraint on amounts held, the actual amount is zero if the desired amount is negative.[4] The desired amount can depend on observed household characteristics included in the vector x_{it}, containing demographics, household income, labor market status, and variables reflecting social security expectations. We will include the variables described in Table 4, plus a set of time dummies. Unobserved time invariant characteristics of the household are captured in the individual effects α_{i}^{j}. The error terms ε_{it}^{j} represent white noise. The individual effects are treated as random effects. Following Chamberlain (1984), they are

[3] If they already receive such income, this is included in Ln_income, and separate income components are not included in the regressions.

[4] For some asset types there are a few households reporting negative amounts. These amounts are set to zero for our analysis.

modeled as the sum of a linear combination of the means of the time varying regressors x_{it} and a component η_i^j assumed to be independent of the regressors:[5]

$$\alpha_i^j = \sum_k \overline{x}_{ik} \lambda_k^j + \eta_i^j$$

The error terms are assumed to be independent over time and independent of both the regressors and the individual effects. Both error terms and individual effects can be correlated across assets. Both the vector of the random components of the individual effects η_i^j (with dimension the number of asset types considered) and the vector of error terms (with the same dimension, in each time period) are assumed to be multivariate normal with zero means and arbitrary covariance matrix.

In this paper, we consider each asset type separately (univariate models) or consider more aggregate asset types, such as all risky financial assets. The same type of model will be estimated for each asset type considered in Section 2. We will also estimate models safe and riskfree financial assets, and for total financial assets.

The Tobit models for panel data can be estimated using maximum likelihood. Conditional on individual effects, the likelihood contribution of a given household can be written as the product of contributions for the various time-periods. Each of these is either a normal density or normal probability. The likelihood contribution for the household is the expected value of this product over the distribution of the individual effects. This integral can be approximated numerically.

Another estimation strategy is quasi maximum likelihood, maximizing the function that would be the log likelihood if all observations were independent (over time, as well as over households), and adjusting standard errors for clustering of observations – accounting for the within household correlations over time. The second estimator is asymptotically inefficient under the assumptions made above, but has the advantage of some robustness against misspecification, since it is still consistent if the error terms are correlated over time. We therefore focus on the results for the second estimator.

[5] The means are taken over the time periods for which the variables are observed. The unbalanced nature of the panel makes a more general approach with an arbitrary linear combination of the time varying regressors as in Chamberlain (1984) infeasible.
[6] Current results use 50 draws for each household.

4. Results

Tables 5-8 present the results for the asset and debt types in Table 1. The dependent variables are the log amounts in real terms, in US $ of 2002, set to zero if the asset or debt type is not owned. The main conclusion is that, in many cases, the asset amounts are correlated with average expected social security amounts (ln_av_hess is often significant), but there is hardly any evidence of an effect of deviations of this expectation with respect to the time mean on the amount held. This suggest that respondents do not react on changes of their perceived entitlements by adjusting their portfolio. There are two exceptions at the two-sided 10 percent significance level: IRAs and Keoghs, and financial debts not related to homes. Households tend to invest more in IRAs and Keoghs in time periods when their expected future benefits are relatively high. A theoretical explanation might be that social security benefits are seen as a safe source of retirement income, and people with a substantial buffer are willing to take more risk (IRAs are usually invested in stocks or stock mutual funds) on their other sources of retirement income.

The other exception is (non-mortgage) home loans. High social security benefit expectations increase the amounts borrowed for home loans, though there hardly any effect on housing, either in the form of primary residence or in the form of other real estate. It thus seems that households whose confidence in safe social security income increases become more willing to finance their housing with this kind of loan, perhaps because they can then use the loan to finance consumption or to invest in potentially high return assets such as IRAs.

The time average of expected social security benefits is positively associated with amounts invested in risky financial assets (stocks, IRAs, other (financial) assets). This can be explained with the argument for using quasi-fixed effects given in Section 1: people with better past performance in the labor market have had a chance to accumulate wealth and also have higher expected benefits. This association is in some sense spurious; if it was not allowed for, it would lead to a strong positive bias on the effect of expected benefits. It is an important advantage of using panel data that such an association can be controlled for, something that would not be possible in cross-section data. On the other hand, the association of average expected benefits with the amount in CDs or in real estate is significantly negative. It is unclear what kind of theory could explain this.

Table 5. Tobit Models - Riskfree Financial Assets

	Checking & Sav.		Bonds		CDs, etc.	
	Coef.	t-val	Coef.	t-val	Coef.	t-val
female	.27	3.13	1.28	1.51	.68	1.46
married	.26	2.39	-.67	-0.66	.61	1.13
edlow	-1.34	-9.58	-2.68	-1.91	-3.52	-4.95
ed1215	-.00	-0.03	.60	0.56	-1.07	-1.89
edhigh	.04	0.38	4.54	4.50	-.72	-1.20
hispan	-.81	-3.98	-8.97	-3.37	-3.27	-3.11
nonwhite	-1.51	-11.73	-4.60	-3.65	-4.20	-6.67
wave94	.05	0.48	1.37	1.27	2.26	4.16
wave96	-.10	-1.05	2.77	2.75	1.22	2.33
wave98	-.14	-1.41	1.87	1.82	1.58	3.12
wave00	.18	1.80	2.32	2.26	2.11	4.15
ybrth	-.06	-8.08	-.29	-3.44	-.13	-2.83
lnincome	.27	6.56	1.54	2.36	.61	3.12
work	-.20	-2.32	-3.44	-4.15	-1.57	-3.50
ln ess	-.07	-1.05	-.79	-1.11	.17	0.56
ln_av_inc	1.36	11.62	6.78	7.87	2.47	5.40
ln_av_hess	.20	2.09	-.14	-0.15	-.94	-2.05
_cons	-8.39	-7.99	-95.18	-12.26	-28.52	-6.39
ln sigma	1.14	86.02	2.83	190.13	2.50	232.81

Notes: Quasi ML estimator for Random Effects Tobit Model;
Ln sigma: estimated log standard deviation of sum of individual effect and error term.

Table 6. Tobit Models – Non-financial Assets

	Housing		Real estate		Business ass.		Transport	
	Coef.	t-val	Coef.	t-val	Coef.	t-val	Coef.	t-val
female	.71	4.71	.25	0.47	.67	0.78	-.09	-1.35
married	2.58	12.75	3.21	4.71	4.91	4.81	1.36	13.77
edlow	-.95	-4.35	-.24	-0.33	.67	0.57	-.50	-4.69
ed1215	.03	0.21	1.25	1.85	-.07	-0.07	.04	0.54
edhigh	.02	0.14	1.40	1.86	-2.28	-2.11	-.33	-3.53
hispan	-1.09	-2.93	-2.29	-2.02	-3.19	-1.79	-.66	-3.83
nonwhite	-1.16	-5.17	-.71	-1.04	-6.50	-5.16	-1.28	-9.92
wave94	-.66	-4.49	3.86	6.60	2.55	3.08	.11	1.38
wave96	-1.17	-8.08	3.53	6.40	.89	1.12	.00	0.02
wave98	-.31	-2.37	1.40	2.53	-.02	-0.04	.03	0.36
wave00	.06	0.48	1.75	3.22	-.02	-0.03	.08	0.97
ybrth	-.08	-5.44	-.06	-1.29	-.04	-0.51	-.01	-1.92
lnincome	.09	1.55	.87	3.38	.16	0.49	.09	2.76
work	-.06	-0.52	-.39	-0.78	5.97	7.27	.00	0.10
ln ess	.07	0.71	-.06	-0.20	-.71	-1.32	.02	0.43
ln_av_inc	1.42	10.72	4.97	7.50	7.29	10.16	.89	11.08
ln_av_hess	.10	0.67	-1.25	-2.42	-1.14	-1.47	-.06	-0.76
_cons	-6.58	-4.58	-61.27	-10.27	-88.66	-11.25	-1.85	-2.24
lnsigma	1.55	91.21	2.61	205.66	2.85	210.06	.95	48.74

Notes: Quasi ML estimator for Random Effects Tobit Model;
Ln sigma: estimated log standard deviation of sum of individual effect and error term.

Table 7. Tobit Models – Debts

	Debt		Mortgage		Home loans	
	Coef.	t-val	Coef.	t-val	Coef.	Std.
female	.94	3.23	-.25	-0.68	.90	1.21
married	-.03	-0.10	1.10	2.59	3.99	4.39
edlow	-1.13	-3.02	-1.17	-2.29	-2.52	-2.36
ed1215	.32	0.90	2.25	5.10	1.43	1.62
edhigh	-.41	-1.11	1.74	3.75	.78	0.85
hispan	.93	1.82	.22	0.32	-2.27	-1.43
nonwhite	1.42	4.18	1.45	3.27	-1.15	-1.14
wave94	.72	2.06	.48	1.30	-.80	-0.95
wave96	.77	2.30	-.38	-1.09	-.51	-0.64
wave98	-.11	-0.32	-.54	-1.57	-.02	-0.03
wave00	-.23	-0.68	-.26	-0.77	-1.23	-1.49
ybrth	.09	3.26	.16	4.44	-.16	-2.44
lnincome	.26	2.47	.15	1.19	.53	1.45
work	1.32	4.69	1.55	4.49	1.77	2.44
ln ess	.04	0.19	.35	1.27	1.28	1.73
ln_av_inc	-.53	-2.31	2.91	9.35	2.79	4.33
ln_av_hess	.49	1.49	.63	1.57	1.01	1.00
_cons	-9.43	-3.57	-51.96	-15.42	-74.80	-10.73
ln sigma	2.21	233.22	2.32	190.77	2.77	236.08

Notes: Quasi ML estimator for Random Effects Tobit Model;
Ln sigma: estimated log standard deviation of sum of individual effect and error term.

Table 8. Tobit Models – Risky financial Assets & Other Assets

	Stocks		IRAs & Keoghs		Other assets	
	Coef.	t-val	Coef.	t-val	Coef.	t-val
female	-.03	-0.11	.76	2.52	.09	0.21
married	-.86	-1.93	.91	2.49	-.57	-1.00
edlow	-4.19	-7.05	-4.00	-8.47	-4.09	-5.15
ed1215	1.11	2.51	.75	2.08	2.47	4.44
edhigh	2.51	5.29	1.83	4.74	4.20	6.97
hispan	-3.65	-3.74	-3.15	-4.38	-2.26	-2.37
nonwhite	-4.96	-9.15	-4.25	-10.23	-3.41	-5.11
wave94	1.17	2.91	.83	2.71	5.29	9.42
wave96	.52	1.39	.43	1.46	2.93	5.37
wave98	.93	2.52	.92	3.18	1.31	2.33
wave00	.44	1.20	1.05	3.65	1.39	2.48
ybrth	-.15	-4.11	-.25	-8.30	.01	0.37
lnincome	.86	4.78	.20	1.84	.35	1.80
work	-2.19	-6.30	-1.22	-4.42	-1.65	-3.59
ln ess	.17	0.64	.36	1.67	-.43	-1.31
ln_av_inc	4.44	10.86	3.31	10.20	4.50	8.92
ln_av_hess	.75	1.71	.89	2.52	.75	1.44
_cons	-60.47	-15.38	-38.20	-11.74	-66.88	-13.26
ln_sigma	2.30	177.39	2.12	158.91	2.52	217.11

Notes: Quasi ML estimator for Random Effects Tobit Model;
Ln sigma: estimated log standard deviation of sum of individual effect and error term.

The results on other explanatory variables are largely in accordance with the empirical literature on the US in general (cf., e.g., Hubbard, 1985, or Bertaut and Starr-McCluer, 2002) and the elderly (Hurd, 2002, or Rosen and Wu, 2002). Hispanics and, in particular, nonwhites hold less financial and non-financial assets than others, while nonwhites also have higher debts. Married couples invest more in most assets than singles, particularly in housing and other non-financial assets. Accordingly, they also have more housing related debt. Investments in most assets increase with education level - even when household income and other factors are kept constant. The education effect is particularly strong for risky financial assets.

The effects of year of birth and the time dummies do not show consistent patterns across asset categories. Of course part of these could reflect age effects (see Gollier, 2002, for theoretical arguments why age may affect portfolio choice), which cannot be separately identified.

The effect of log household income is always positive (even for financial debt) and often significant. The effect of "permanent income" (measured as the sample average over time) is also positive and still much stronger in all cases but financial debts. Permanent income proxies past savings and wealth accumulation potential. Dropping it from the regression would lead to substantial overestimation of the direct income effect. On the other hand, for financial debt not related to housing, permanent income has a significant negative effect, suggesting that consumer debt is mainly held by households with low permanent income.

Table 9 presents estimates for a Tobit model of total financial assets. It presents the results of both estimation strategies discussed in the previous section. The results are quite similar, suggesting some robustness of these findings. An advantage of the ML estimator is that it also indicates the importance of individual effects – they explain slightly more than half of the unsystematic part of the dependent variable, with an estimated standard deviation that is somewhat larger than that of the error term.

The main conclusion is the same as before: there is a significant positive association with the average expected amount of social security benefits over all the sample waves, but keeping that constant, there is no effect of high expected benefits in a specific period on financial assets in that period.

Table 9. Tobit Model for Total Financial Assets
ML and Quasi ML estimates

	Maximum Likelihood		Quasi ML	
	Coef.	T-val	Coef.	T-val
female	.26	2.89	.32	3.62
married	.21	1.77	.39	4.35
edlow	-1.74	-11.52	-1.85	-15.77
ed1215	.10	0.99	.17	1.55
edhigh	.33	2.74	.45	3.81
hispan	-1.09	-4.92	-1.25	-7.57
nonwhite	-1.89	-13.90	-2.01	-17.87
wave94	-.06	-0.63	-.33	-4.16
wave96	-.23	-2.44	-.42	-5.70
wave98	.05	0.63	-.13	-1.83
wave00	.31	3.36	.13	1.69
ybrth	-.09	-10.82	-.11	-12.60
lnincome	.25	6.08	.23	9.82
work	-.42	-4.52	-.18	-2.66
ln_ess	-.02	-0.33	-.02	-0.53
ln_av_inc	1.78	13.36	1.74	26.83
ln_av_ess	.32	3.05	.26	3.19
_cons	-11.23	-9.45	-9.58	-12.47
ln sigma	1.115	78.11		
sigma_u			2.45	67.53
sigma_e			1.96	103.11

Ln sigma: estimated log standard deviation of sum of individual effect and error term.
Sigma_u: estimated standard deviation individual effect
Sigma_e: estimated standard deviation error term

Table 10 presents ML estimates for risky and safe financial assets. The category of risky financial assets comprises stocks (and stock mutual funds) and IRAs. The category of safe financial assets has CDs, bonds, and checking and saving accounts. There is a weak positive effect of expected social security benefits on investments in risky financial assets, but the effect is not significant. On the other hand, there is a much clearer and significant positive effect of the average expected benefits amount on risky assets. This may have several interpretations. One is that this average amount proxies past economic resources creating potential for wealth accumulation, and this type of “extra” savings goes often into risky assets. Another interpretation would be that optimistic people have higher benefit expectations and also invest more in risky assets. There is no effect of either the temporary component or the permanent component of expected benefits on safe financial assets.

The individual effects are substantial for both types of assets. They explain 47% of the unsystematic variation for safe assets, and 70% for risky assets. This

suggests a lot of persistence in risky asset holdings, which would be in line with substantial transaction costs but also with the notion that the risk return trade-off for stocks is better if assets are held over a long time period.

Other results in Table 10 largely confirm findings in the literature. For example, there is a strong association of both types of financial assets with permanent as well as transitory income, and the relation is stronger for risky than for safe assets. This implies that the share of risky assets in the total household portfolio will increase with both permanent and transitory income

Table 10. Tobit Model for Safe and Risky Financial Assets

	Risky		Safe	
	Coef.	t-val.	Coef.	t-val
female	.98	4.05	.32	3.65
married	.93	4.17	.33	3.60
edlow	-4.01	-12.25	-1.55	-13.34
ed1215	.92	3.19	.00	0.01
edhigh	1.56	5.14	.17	1.50
hispan	-3.15	-6.48	-.96	-5.76
nonwhite	-4.41	-13.57	-1.73	-15.90
wave94	-.29	-1.60	-.14	-1.62
wave96	-.48	-2.82	-.25	-2.95
wave98	.19	1.12	-.25	-2.85
wave00	.26	1.50	.10	1.19
ybrth	-.22	-9.94	-.08	-10.20
ln_income	.34	5.63	.26	9.69
work	-.6	-4.19	-.13	-1.79
ln ess	.14	1.17	-.04	-0.71
ln_av_inc	3.13	17.01	1.45	21.72
ln_av_ess	.84	4.03	.11	1.29
_cons	-33.62	-16.07	-7.41	-9.67
sigma_u	6.07	54.84	2.20	53.75
sigma_e	3.91	85.44	2.31	100.99

Notes: ML estimates
Sigma_u: estimated standard deviation individual effect
Sigma_e: estimated standard deviation error term

[7] If we do not allow for such a correlation, we find somewhat higher income elasticities, 0.24 and 0.54.
[8] See Bloemen (2002) for similar findings in the context of wealth effects on labor market transitions.
[9] If we do not allow for such correlations, we find somewhat higher effects of the future pension dummy and much higher effects of expected social security income.

Conclusions

This paper has analyzed household portfolio choice for an elderly cohort followed during the years before and just after retirement. The main emphasis was on the effect of expected social security benefits on ownership and amounts held. We found associations with the permanent component of these expected amounts, but we found hardly any evidence of an effect of temporarily high expected amounts on holdings in a specific period. This is generally a robust finding, for many types of assets. The only exception may be an effect on IRAs, which would be in line with the notion that a safe buffer in the form of high expected social security benefits makes it easier to take some risk with other retirement resources, benefiting from tax advantages as well as the equity premium.

Our findings can be seen as reassuring for those who think that high social security benefits have a negative effect on private provision of retirement resources. If anything, the effects of social security benefits on several forms of wealth accumulation are positive, while the "substitution" effect would be negative.

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