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Forecasting Labor Force Participation and Economic Resources of the Early Baby Boomers

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Abstract

This paper forecasts the retirement patterns and resources of the Early Baby Boomers by estimating forward-looking dynamic models of labor force participation, wealth accumulation and pension and Social Security benefit claiming for older workers using seven waves of HRS-data. The two most important innovations of our proposed approach are the use of alternative measures of pension entitlements and the associated incentives, and accounting for subjective expectations about future work. Our main findings are that the Early Baby Boomers will work longer and claim Social Security later.

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1. Introduction

The last decade has witnessed a marked reduction in the generosity of retiree benefits, notably with the termination of defined benefit (DB) plans and their replacement with defined contribution (DC) plans which shift the investment risk to the worker. According to a report by the Congressional Research Service (CRS, September 2007) on "Pension Sponsorship and Participation" the percentage of private-sector workers between the ages of 25 and 64 who participated in employer-sponsored retirement plans fell from 50.3 percent to 43.2 percent.[1] An important policy question is how these trends will affect the material well being of future retirees.

Labor force participation rates at older ages have increased over the last decade. Figure 1 shows labor force participation rates from the Current Population Survey (CPS) of men by age group and how it evolved since 1990. For example, the labor force participation rate of men 60-64 rose from 55.5 percent in 1990 to 58.6 percent in 2006. The increase was even greater – 26.0 percent to 34.4 percent – for those aged 65-69. Trends for women have been similar. Hurd and Rohwedder (2008) suggest that part of this increase is due to the shift in employer-provided pensions from DB to DC. Michaud and van Soest (2008) find that also the elimination of the Social Security earnings test has contributed to this trend. Other factors may well have been at work at the same time, such as improvements in health.

Whether these trends towards longer working lives continue is an important question for policy makers because of its direct impact on Social Security and Medicare finances on the one hand and on financial well-being of future retirees on the other hand. In this paper we investigate the question of future labor force participation for the next cohort of retirees: the Early Baby Boomers, that is, those born between 1948 and 1953. For that purpose we develop a dynamic model of labor force participation consistent with forward-looking behavior. We provide reduced form estimates and leave estimation of the full-fletched model to future work.

[1] Statistics are based on CPS data.

The literature on estimating retirement models is extensive, covering a wide array of approaches ranging from static to dynamic models, and from structural to reduced form estimation. Our model, while not being a fully dynamic, structural model of retirement, is in the spirit of structural models as exemplified in the work of Gustman and Steinmeier (1986), Rust et al. (2001) and French (2005). Estimation of a fully structural model with pensions, Social Security claiming, savings and work decisions under uncertainty has not been accomplished. We will incorporate all of those elements by using an approximation to complex decision rules derived from this type of models, following Keane and Wolpin (2002) who applied this method in another context, and Blau (1998) on joint labor force decisions of couples. We see this approach as complementary to the structural approach for informing policy makers about future retirement patterns and resources of the elderly.[2] We consider two important extensions of prior work:

First, we use innovative methods of measuring pension entitlements that allow performing our analysis on full, population-representative samples: the assessment of the impact of pensions on retirement in general-purpose surveys has been difficult due to data limitations, such as missing information on the variables of interest, measurement error, etc.[3] We use pension information derived from respondents' self-reports in a way that reduces the effect of missing information and measurement error (in particular in reports on plan type). Chan and Stevens (2004) argue that such self-reported information enhances the identification of the effects of pension incentives on retirement behavior.[4]

Second, we account for individuals' subjective expectations about future work. In face of extended life spans and increasing risk born by the individual (investment risk in

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[2] The main disadvantage of our approach is that we cannot consider counterfactual experiments for policies that have not occurred in the past as well as policies for which a clear policy-lever cannot be identified from approximation to the decision rules. For example, assessing the effect of a large reform such as introducing retirement accounts is better analyzed within a structural model at the expense of simplifications in the choice environment of individuals (e.g. Gustman and Steinmeier, 2004). On the other hand, Keane and Wolpin (2002) discuss the type of policies for which approximations can be informative.

[3] Prior studies have relied on samples with matched administrative information on pension structure, at the cost of being left with substantially smaller and potentially selected samples (e.g., Kotlikoff and Wise, 1989; Gustman and Steinmeier, 2004).

[4] Chan and Stevens (2004) have estimated models of retirement expectations as a function of future pension gains derived from self-reports. In the case of missing information they exclude the affected observations, resulting in a selected sample for analysis.

DC plans and rising cost of medical care) future retirees may consider working longer. Integrating expectations about future work in our model is therefore important, given our goal to use our estimates to forecast retirement patterns and economic resources for the Early Baby Boomers. Our estimations use seven waves of HRS data.[5]

To verify the fit of the reduced-form version of the model we simulate outcomes for the 1931-1941 cohort from 1992 to 2004 and compare with observed outcomes from the data. Overall this comparison is very favorable, while still leaving some room for improvements, notably in the profile of Social Security claiming at ages 62, 63 and 64, and the profile of median wealth.

Comparing predicted patterns of the Early Baby Boomers with the original HRS cohort we find that the Early Baby Boomers will work longer and claim Social Security later. The differences are larger for women than for men.

2. Data

The data for the current analysis are from the Health and Retirement Study (HRS) (Juster and Suzman, 1995), a survey funded by the National Institute on Aging, with additional funding from the Social Security Administration. The HRS is a biennial longitudinal survey of individuals 51 or older. Data from eight waves, fielded from 1992 through 2006, have been collected; each wave has close to 20,000 interviews. The sample is representative of the U.S. population, except for certain oversamples, for which weights are used to calculate population averages. In the initial wave the target population was from the cohorts born in 1931 through 1941, and they were approximately aged 51-61 at interview. In 1998 new cohorts were added making the HRS representative of the population aged 51 or over. In 2004 new cohorts aged 51-56 were again added, the so-called Early Baby Boomers.

The HRS questionnaire has sections on health, economic status, labor market activity, and family linkages, among other topics. Respondents report labor force status,

[5] Over this period the original HRS cohort (aged 51-61 at baseline in 1992) has almost completed its full transition into retirement. The estimation of pension entitlements uses some additional information from the latest wave of HRS (wave 8 collected in 2006).

information about employment, and, if working, whether they participate in a pension on their job. If they do participate, they report their pension plan type (DB, DC, or both) and the age at which benefits are fully available as well as any earlier age at which they may be partially available.

2.1 Estimating Pension Entitlements

To measure pension entitlements we use an innovative method developed at RAND by Hurd and Rohwedder for which some first results are presented in Hurd and Rohwedder (2007). The estimation is implemented in a way that reduces the impact of misreported plan type and missing information, both of which have posed major barriers in the past to using the self-reports on pensions. The point of departure is that the most accurate and most complete report on pension entitlements is obtained immediately after a respondent leaves a job,[6] i.e., when she just had to make important decisions about the disposition of the pension. At this time HRS collects a full inventory of pension type and values. With the original HRS cohort having almost completed its transition into retirement we have a full set of self-reports on pension entitlements at various points in time leading up to the separation from a job (often associated with retirement), and observations on the realizations of pension entitlements for this cohort. Relating these outcomes to prior self-reports, Hurd and Rohwedder obtain estimates of the probabilities of claiming benefits from a pension at a certain date in the future, and the associated amounts. Estimation takes into account self-reported eligibility ages, and rich sets of covariates relating to pension entitlements (see Appendix 1 for more detail).[7]

2.2 Social Security Entitlements

[6] Leaving a job does not have to coincide with retirement. Over the eight waves of HRS that are currently available, there are about 4,000 separations from the job held in 1992 that involve the disposition of at least one pension plan.
[7] It can be augmented to also take into account information from employer-provided summary plan descriptions.

To estimate Social Security entitlements at possible future claiming ages we use Social Security earnings and apply the Social Security rules.[8] For respondents who gave consent, we have access to Social Security administrative records on their earning histories. The fraction having given consent varies by cohort (75% for HRS respondents, 65% for Early Boomers). Kapteyn et al. (2006) and Haider and Solon (2000) report quite mild selection effects when analyzing the characteristics associated with a match; so we do not make any adjustment to the weights when producing statistics in this paper.[9]

The information contained in the earnings history file allows computing the average indexed monthly earnings (AIME) which is the basis for the computation of Social Security benefits. It is calculated as the average of the highest 35 years of earnings. Earnings are indexed to wage growth. We also determine who is eligible to Social Security benefits by using the associated quarters of coverage. If a respondent has accrued at least 40 quarters of coverage by age 62, he or she is eligible for Social Security benefits.

3. Trends in Outcomes and Initial Conditions across Cohorts

Our estimations below impose a fair amount of complex structure on the data to arrive at predictions of the labor force participation and resources of the Early Baby Boomers.' Examining trends in the raw data, both for outcomes as well as for control variables, gives a preview of what we might expect to find from in our model estimations (and also a reality check). In Table 1 we present descriptive statistics for females and males from three different birth year cohorts observed in the HRS survey when they were age 51 to 56: "HRS" stands for the original HRS cohort born between 1936 and 1941;[10] "WB" denotes the War Babies born between 1942 and 1947 and "EBB" are the Early Baby Boomers who were born between 1948-1953. At ages 51 through 56 each of these birth year cohorts was newly inducted to the HRS survey, so the statistics do not suffer

[8] Social Security earnings files are restricted data. We use these under the provisions of the Umbrella Data Protection Plan established between HRS Michigan and the RAND Center for the Study of Aging.
[9] In future work we plan to incorporate this adjustment.
[10] The original HRS cohort included additional birth years, those born between 1931 and 1935, who were between age 57 and 61 at baseline.

from attrition bias. Note that any of the comparisons will be cross-section that mix time and cohort effects. This does not matter for our purposes, however, as we are interested in finding differences in the initial conditions of the three cohorts.

Labor force participation. For males there are only very small differences across cohorts suggesting a slight drop in labor force participation from one cohort to the next. Among females we notice an increase in labor force participation from 63.7 percent to 73.5 percent reflecting the fact that younger cohorts of females have a stronger attachment to the labor market. Especially the fraction of females working full-time has increased in about the same manner as the portion not in the labor force has fallen. Looking at job types the fraction of blue-collar jobs has decreased for both sexes. These trends would suggest that among women we would expect later retirement for younger cohorts in our more detailed analysis below.

Health. For the HRS cohort in 1992 we find a fairly large difference between males and females in the fraction reporting fair or poor health, with females appearing in worse health (20.6 vs. 16.5 percent). However that difference shrinks to almost nothing among 51 to 56 year olds in 2004 when the fraction of males in fair or poor health (21.2 percent) has caught up to about the same level observed among females (22.8 percent). These developments are also reflected in the increasing rates of mild health conditions such as high blood pressure, diabetes and respiratory problems. In summary, later cohorts in their early 50s appear to be in worse health, with the trend being more pronounced among men posing potential impediments to staying in the labor force longer.

Expectations. The subjective probabilities of working past age 62 and the subjective probabilities of working past age 65 are higher for successive cohorts, both for male and female workers, pointing again towards potentially longer working lives for the Early Baby Boomers.

Pensions. Pension coverage (having any pension on the job) has increased for women (52.9 percent in 1992; 58.0 in 2004), while remaining about the same for males across cohorts. The well-known shift in employer-provided pensions from DB to DC plans is clearly visible in these tables. The fraction of workers reporting a DB plan on their current job has dropped from 34.9 to 28.5 percent among female workers and from 42.4 to 30.4 percent among male workers. This trend is mirrored by a similar upward trend in the fraction reporting a DC plan on the current job. The value of pension wealth entitlements from the current job is larger for later cohorts at the mean, but at the median the picture is more mixed. At the median we only observe clear increases among female workers.

Wealth. "Males living in couples" is the only group that shows trends of strictly increasing wealth at the mean across cohorts, both for financial and non-housing wealth. However, even for them a different picture of either flat or slightly lower wealth emerges when looking at medians. For all other groups, means and medians show mixtures of higher and lower wealth across cohorts. From these patterns it is difficult to make a prediction with respect to future retirement patterns. Heterogeneity is likely to be important.

4. Econometric Model

The conceptual framework underlying our analysis is consistent with a structural life-cycle model such as in Gustman and Steinmeier (1986), Rust et al. (2001) or Blau (2005): the individual is assumed to maximize lifetime utility. In any given period the individual chooses whether to work and the amount (part-time or full-time) and consumption (wealth accumulation);[11] we augment this with the choice of whether to claim benefits from Social Security. Because retirement is increasingly less observed to be an absorbing state we allow individuals to return to work, part-time or full-time.

[11] The measure of wealth accumulation includes assets held in DC plans on the current job.

Keane and Wolpin (2002) show the feasibility, in simulation and in application, of estimating an approximation of a forward-looking structural model.[12] This simplification is suitable to our analysis, since our goal is to forecast the retirement patterns and resources of Early Baby Boomers under the current regime.

We use an approximation to the decision rules leading to a multiple-decision dynamic panel data model. The decision rules, which are formulated to be consistent with a forward-looking model, depend on the state at the beginning of a given period and incorporate forward-looking measures of incentives such as accruals or option values of delaying claiming Social Security benefits and expected pension wealth. We consider three decisions for an individual in period *t*: work $y_{it,w}$ (none, part-time, or full-time work); the binary decisions of claiming Social Security benefits $y_{it,s}$ and assets $y_{it,a}$. Denote by $Y_{it} = (y_{it,w}, y_{it,s}, y_{it,p}, y_{it,a})'$ the vector of decisions for period *t*. Since some of these outcomes are binary we model them as a mapping from a latent index y_{it}^* which is the approximation to the net value function of each alternative from a forward-looking problem:

$$y_{it}^* = \Phi(x_{it}) + \Gamma y_{i,t-1} + \Upsilon f_{it} + \eta_i + \varepsilon_{it}.$$

The vector $\Phi(x_{it})$ represents the dependence of decision rules on a vector of standard observable characteristics x_{it} (such as socioeconomic status and health), f_{it} is a vector of forward-looking measures of incentives related to pensions and Social Security benefits. The approximation includes lagged decision variables in the specification which is in contrast to static models of retirement behavior. This is consistent with models that include transition costs for labor market transitions and allows for feedback effects from one decision to the other over time.[13] Finally, η_i is a vector of individual specific unobserved heterogeneity and ε_{it} captures shocks that can be serially correlated.

Not all decisions are made every period because of specific program rules (e.g., early and normal retirement ages in Social Security and pension plans). Hence the

[12] Estimation of a fully structural model such as ours would be computationally intensive and a multi-year undertaking.
[13] There are trivial restrictions imposed on Γ for decision variables (SS and DB pension claiming) pertaining to absorbing states. Lagged claiming status does not enter the claiming equation.

decision rule is not the same for every individual and year. In particular, $y_{it} = G(y_{it}^{*}; y_{it-1}, w_{it})$ where w_{it} are characteristics that determine the choice set in year t and *G* is the mapping from latent indices to decisions. Such a model provides a rich view of the dynamics in decisions made by individuals in the HRS. Estimation is by simulated maximum likelihood (e.g. Michaud, 2005) using seven waves of HRS data.[14]

In each equation, we include an extensive set of covariates controlling for demographics, health and job characteristics. Table 2 gives sample means and standard deviations for the estimation sample. The estimation sample consists of respondents initially observed working in the age group 51-56. We conduct separate analyses for females and males.

We distinguish three labor market states: full-time (working 30+ hours a week), part-time work and inactivity. The "inactive" include the disabled and those unemployed. Social Security benefit claiming status is defined from self-reports on when benefits were first claimed.

Wealth is defined as the sum of financial (checking and savings, CDs, stocks, bonds and IRAs) and real components (housing, etc). All monetary amounts are expressed in 2004 US dollars. Since the wealth distribution is skewed, a transformation is necessary to forecast adequately the evolution of the distribution of wealth. Because of non-linearities in the dynamic model, it is not sufficient to predict the mean correctly. We use a generalization of the inverse hyperbolic sine transform, proposed MacKinnon and Magee (1990). First denote the variable of interest y, here wealth. The hyperbolic sine transform is

$$y = \sinh(x) = \frac{\exp(y) - \exp(-y)}{2}$$

The inverse of the hyperbolic sin transform is

$$x = \sinh^{-1}(y) = h(y) = \log(y + (1 + y^2)^{0.5})$$

This transformation allows dealing with respondents with zero or negative wealth. For large values of *y*, it coincides with the log transformation. However, this transformation is

[14] Michaud (2005) shows how simulations from such a model (of work and SS claiming) for couples match closely observed outcomes in the HRS while a static model does a poor job. By allowing for heterogeneity, such model also allows disentangling time-invariant heterogeneity from true state-dependence effects which are important when forecasting future retirement profiles.

too rigid to capture the extreme skewness of the distribution of the long right tail. We can generalize such transformation, first allowing for a shape parameter θ ,

$$r(y) = h(\theta y)/\theta$$

The additional parameter allows correcting for the extreme skewness. We can then specify the regression model as

$$r(y) = x\beta + \varepsilon, \varepsilon \sim N(0,\sigma^2) .$$

A further generalization is to introduce a location parameter γ such that the new transformation becomes

$$g(y) = \frac{h(\theta y + \gamma) - h(\gamma)}{\theta h'(\gamma)}$$

where $h'(\gamma) = (1+\gamma^2)^{-1}$. We can specify the same regression model in terms of the transformation g. The shape parameters can be estimated from the concentrated likelihood for θ, γ . Upon estimation, we can simulate

$$\tilde{g} = x\hat{\beta} + \sigma\tilde{\eta}$$

where η is a standard normal draw. Given this draw, we retransform to obtain

$$h(\theta y + \gamma) = \theta h'(\gamma)\tilde{g} + h(\gamma)$$
$$\tilde{y} = \frac{\sinh[\theta h'(\gamma)\tilde{g} + h(\gamma)] - \gamma}{\theta}$$

Based on preliminary estimates, we select $\theta = 1/15, \gamma = 3/4$. These are held fixed in estimation. In future work, we will estimate these parameters jointly with other parameters of the model.

Controls other than lagged variables and initial conditions can be divided into three groups. For most outcomes, we use the initial value so that we will not need to model their age pattern in the simulations.

First, we consider the measure of expected pension wealth constructed as discussed above. We take logs as to minimize the effect of outliers. We include an indicator for whether someone reports having at least one plan and whether he is currently eligible to at least one pension plan. We complement the controls for private pension wealth with controls that capture Social Security wealth. We control separately for the average indexed monthly earnings, the lifetime earning measure used to compute Social Security benefits, and quarters of coverage. We also include the wage rate at baseline, the spouse's income and other household income.

The second group of variables consists of demographics such as age, race and ethnicity, marital status, living arrangements and education. Health enters the estimations in three ways. First, we consider whether the respondent self-reports being in fair or poor health. We add whether the respondent has been diagnosed in the past with a severe condition such as heart disease, stroke or cancer. We do the same for milder chronic conditions such as diabetes, hypertension and respiratory problems. Finally, we include measures of disability such as having IADL or ADL limitations. All these health variables are measured at baseline.

The last group of controls captures individuals' expectations: the subjective probability of working past age 62 and 65, asked at baseline, enters as a control for labor force participation expectations; and the subjective probability of living past age 75 as a control for the time horizon of the respondent which may affect his decisions. These expectations play an important role in forecasting future retirement patterns in that they capture changes in the environment or other factors that may be changing over time in a way that the model cannot capture relying only on observed current trends.[15] Hurd (1999) documents the predictive power of these subjective expectations for subsequent retirement behavior. Hurd and Rohwedder (2008) estimate that changes in pension coverage, plan type and benefit eligibility ages explain some of the change in anticipated employment as measured by subjective probabilities, but not all.

Because, we cannot effectively control for all relevant variables influencing respondents' outcomes, we allow for correlation in unobserved heterogeneity. We assume this term can be decomposed into a time-variant and permanent component

$$u_{it} = \eta_i + \varepsilon_{it}$$

[15] For example, individuals may perceive changes in uncertainty with respect to the receipt or generosity of their pensions or changing conditions or attitudes about working at older ages.

where $\varepsilon_{it} \sim N(0,\Sigma_\varepsilon)$. The permanent unobservables η_i are potentially correlated with the initial state y_{i0}, which is known as the initial conditions problem. We assume that $\alpha_i \sim N(\Pi y_{i0},\Omega_\eta)$ where $\alpha_i = \eta_i - \Pi y_{i0}$ is the residual of the linear projection. This is the initial conditions solution proposed by Wooldridge (2000, 2005). One could experiment with more flexible functional forms.

Each outcome is observed according to a non-invertible mapping $g_k(y_{it}^*)$ The likelihood contribution of individual *i* is given by

$$\Pr(y_i \mid w_i;\theta) = \int_{v \in B(y_i, w_i, \theta)} dF(v_i;\Omega_{vi})$$

where $v_i = \iota_T \otimes \alpha_i + \varepsilon_i$, $(\varepsilon_{i1}',...,\varepsilon'_{iT})'$, $w_i = (x_{i1},...,x_{iT}, z_i, y_{i0})$ and $B(y_i, w_i, \theta)$ denote the bounds of the set of errors consistent with data y_i, w_i for parameters $\theta = (\Phi(),\Gamma,\Upsilon,\Pi,\text{vech}(\Sigma_\varepsilon),\text{vech}(\Omega_\alpha))$. The size of the integral depends on the sequence observed because death truncates the observation of other outcomes. For year t, errors v_{it}, and employment outcome j the vector of errors to model is given by

$$\tilde{v}_{it} = M_j v_{it}$$

where M_j is a block diagonal matrix

$$M_j = \begin{pmatrix} I_4 & 0_{4\times J} \\ 0_{J-1\times 4} & D_j \end{pmatrix}$$

with D_j an $J-1$ identity matrix with a column filled with -1 inserted at position j. Creating a block diagonal matrix with these transformation matrices leads to the transformation

$$\tilde{v}_i = M_i v_i$$

and it follows from the random effects assumption that

$$\Omega_i = \text{var}(\tilde{v}_i) = M_i(J_{T_i} \otimes \Omega_\alpha + I_{T_i} \otimes \Sigma_\varepsilon)M_i'$$

where J_{T_i} is a matrix of ones (size T_i). The integral can be simulated using the GHK simulator (see Train, 2002). We use 10 Halton draws and compute panel robust standard errors using the Sandwich estimator of the covariance matrix.

We use the estimates from our model, which is mainly estimated over individuals of the original HRS cohort (age 51-61 in 1992) and those from the War Babies cohort (born between 1942-1947), to produce out-of-sample predictions of the Early Baby Boomers' retirement patterns and retirement resources, given their observed characteristics and expectations in 2004.

5. Results

5.1 Estimation Results

In this version of the paper we provide reduced form estimates of the dynamic model developed above. We estimate separately a multinomial probit of labor force participation, a OLS of transformed wealth (using the inverse hyperbolic sine transform) and a probit of Social Security claiming. Hence, we assume no correlation in unobservables between the equations.

We first discuss the parameter estimates we obtain from estimation. Coefficients along with t-statistics are presented in Tables 3 and 4 for females and males, respectively. The magnitudes are difficult to interpret since some of the parameters are only identified up to scale (in the probit and multinomial choice model). However, we can discuss the sign and the statistical significance of some of the key covariates. We focus on those that appear to affect the outcomes of our forecasts in important ways:

We estimate the state-dependence and feedback effects to be quite large and strongly significant (many of the lagged variables are significant at the 1-percent level). For males, wealth and pension wealth show the anticipated sign consistent with an income effect on participation. Indicators of bad (or worse) health generally have a negative effect on labor force participation and wealth accumulation. These effects appear to be more pronounced for women with parameter estimates on several health variables being significant at the 1-percent level. The subjective probabilities of working past age 62, which we include to capture factors that we cannot capture with the other variables in our model, strongly affect labor force attachment, both for men and women.

5.2 Goodness-of-Fit

To assess whether the model produces sensible forecasts, we conduct the following experiment. We use as a baseline those aged 51 through 56 in 1992 and simulate their outcomes over the 90s until 2004. We then compare actual and simulated profiles for full-time work, Social Security benefit receipt and median wealth. Figures 2, 3 and 4 show the results. The fit is generally good but some areas remain to be improved, particularly the profile of Social Security claiming at ages 62, 63 and 64, and the profile of median wealth.

5.3 Forecast for the Early Baby Boomer Cohort

Figure 5 shows the age profile of the forecasts of labor force status for the Early Baby Boomer cohort by sex. For example, at age 60 about 55 percent of males of this cohort are predicted to work full time and about 20 percent at age 65. The figures for working full time are very similar among women, but in addition they engage in more part time work. As a result when focusing on “any work” (i.e. taking full-time and part-time together) we find that labor force participation among women is *higher* than that for men at any age up to about age 67.

Figure 6 shows the forecasts of Social Security benefit receipts for men and women by age. At age 62 about 67 percent of women will have claimed Social Security; that is a higher fraction than is forecast for men (about 60 percent). This difference largely disappears at age 63 when many more men are predicted to have claimed their benefits.

Comparison with Older Cohorts

Figures 7 and 8 compare these forecasts to simulations for the older HRS cohort. Note that the estimates underlying the simulations for the HRS cohort directly reflect the actual experience of that cohort. We find that Early Baby Boomers are predicted to engage in full-time work at substantially higher rates well into their mid-sixties. The difference is larger for women and applies to an earlier age range: between ages 55 and 63 the fraction of women working full-time is predicted to be almost 10 percent higher on average; from age 64 to 66 it is about 5 percent higher than that of the HRS cohort. For males the differences are mostly concentrated in the sixties but reach well into their seventies; they amount to predicted increases in full-time work of about 5 percentage points on average.

In summary, these forecasts suggest a continuation of the trends observed in CPS data to date (Figure 1); that is, trends towards higher labor force participation for men and women, in particular at older ages.

Figure 8 shows similar patterns for Social Security benefit receipt: the Early Baby Boomers are predicted to claim benefits later, and the difference is a little more pronounced for women.

We find no clear patterns for wealth (not shown). This is not particularly surprising. While the raw data showed strong increases in wealth across cohorts for males living in couples the trends seemed more mixed for all other groups, and in particular at the median. In addition, wealth inequality appears to be greater among Early Baby Boomers than among the HRS cohort when they were the same age.

6. Conclusions

Our objective in this work has been to forecast the retirement patterns and resources of the Early Baby Boomers to answer the question whether recent trends of increased labor force participation at older ages will continue.

To that end we developed a forward-looking dynamic models of labor force participation, wealth accumulation and pension and Social Security benefit claiming for older workers using seven waves of HRS data. The two most important innovations of our approach were the use of alternative measures of pension entitlements and the associated incentives, and accounting for subjective expectations about future work.

We estimated a reduced from version of the model and the parameter estimates from the model show significant effects for many of the key variables and with the anticipated sign. This is also the case for the subjective expectations about future work that we included. We verify the fit of the model by simulating outcomes for the 1931-1941 cohort from 1992 to 2004 and comparing with observed outcomes from the data. The result is favorable and so we turned to forecasting the outcomes for the Early Baby Boomers: they are predicted to engage in full-time work at substantially higher rates well into their mid-sixties. The differences are sizeable, in particular for women: between ages 55 and 63 the fraction of women working full-time is predicted to be almost 10 percent higher on average; from age 64 to 66 it is about 5 percent higher than that of the HRS cohort. For males the differences appear mostly in their sixties but reach well into their seventies; they amount to increases in full-time work of about 5 percentage points on average across this fairly wide age range.

In summary, these forecasts suggest a continuation of the trends observed in CPS data which imply higher labor force participation for men and women, in particular at older ages.

In future research we aim to implement the estimation of the fully-dynamic forward looking model that we developed, and to find the relative contribution of those factors that we model directly compared to factors that lie outside of our model, but are accounted for by including individuals' subjective expectations about future work in our estimations.

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Table 1: Cohort comparisons: 51-56 year olds in 1992 (HRS), 1998 (WB) and in 2004 (EEB), weighted. Amounts in thousands of $2004.

		Female			Male	
Variables	HRS	WB	EBB	HRS	WB	EBB
Survey year	1992	1998	2004	1992	1998	2004
Individual characteristics						
Work for pay	0.637	0.693	0.735	0.826	0.821	0.813
full-time	0.430	0.482	0.513	0.719	0.726	0.718
part-time	0.202	0.205	0.216	0.106	0.092	0.092
not in labor force	0.363	0.307	0.265	0.174	0.179	0.187
self-rated health fair/poor	0.206	0.216	0.228	0.165	0.179	0.212
severe health condition	0.163	0.190	0.189	0.166	0.192	0.179
mild health condition	0.445	0.465	0.529	0.454	0.525	0.534
subj. prob. work past 62*	40.9	43.3	45.9	48.5	53.7	55.3
subj. prob. work past 65*	22.2	26.2	29.4	27.9	34.1	36.4
subj. prob. live past 75	66.4	69.0	66.1	62.9	62.6	61.3
Current job characteristics*						
professional job	0.310	0.363	0.379	0.370	0.384	0.391
white collar job	0.528	0.508	0.491	0.233	0.235	0.238
blue collar job	0.162	0.129	0.129	0.397	0.381	0.370
any pension	0.529	0.562	0.580	0.617	0.636	0.592
any DB	0.349	0.313	0.285	0.424	0.398	0.304
any DC	0.275	0.374	0.420	0.345	0.426	0.459
pension wealth mean	53.5	55.4	63.5	153.7	166.5	202.0
median	53.5	55.4	66.6	77.2	80.9	66.1
Household characteristics ($'000)						
Couples - means						
financial wealth	87.8	118.5	104.7	71.3	88.5	116.9
non-housing wealth	274.3	301.2	288.5	244.7	275.9	325.5
Singles - means						
financial wealth	30.3	43.2	35.0	92.0	57.4	61.4
non-housing wealth	64.2	96.4	87.4	195.5	142.1	128.2
Couples - medians						
financial wealth	16.7	20.0	12.0	14.7	13.9	11.0
non-housing wealth	78.6	101.0	79.5	74.7	71.4	71.0
Singles - medians						
financial wealth	1.1	0.7	0.3	5.1	1.3	1.5
non-housing wealth	9.1	11.0	8.5	25.3	18.5	14.0
N	*6163*	*4988*	*2392*	*5323*	*2691*	*1548*

Authors' calculations. Weighted.
*Statistics related to current employment computed over working people only.

Table 2: Descriptive Statistics for Estimation Sample

	Female		Male	
Variables	Mean	Std. Dev.	Mean	Std. Dev.
outcomes				
full-time	0.609	0.488	0.776	0.417
part-time	0.255	0.436	0.088	0.284
transformed wealth	34.397	26.016	37.368	25.343
controls				
log pension wealth	10.361	1.276	11.138	1.444
age/10	0.516	0.177	0.524	0.178
age/10 squared	0.298	0.193	0.306	0.196
married	0.673	0.469	0.874	0.332
widowed	0.072	0.259	0.012	0.108
other adults living in hh	0.492	0.500	0.553	0.497
non-labor income/1000	38.889	42.082	35.658	40.663
severe hlt condition	0.121	0.354	0.120	0.354
mild hlt condition	0.377	0.583	0.404	0.579
1 iadl	0.063	0.243	0.055	0.228
1-2 adl	0.044	0.206	0.031	0.172
self-reported hlth poor	0.115	0.320	0.114	0.318
black	0.172	0.378	0.102	0.303
hispanic	0.053	0.224	0.074	0.262
less than high school	0.154	0.361	0.153	0.361
college education	0.439	0.496	0.491	0.500
career occupation	0.777	0.416	0.747	0.435
professional job	0.327	0.469	0.349	0.477
blue-collar job	0.174	0.379	0.414	0.493
# quarters coverage	89.168	34.358	122.694	31.901
log AIME	0.700	0.104	0.795	0.078
wage rate	15.670	15.663	23.023	22.162
any pension	0.605	0.489	0.670	0.470
subj. prob work past 62	41.491	37.903	47.967	39.152
subj.prob work past 65	22.301	31.644	27.170	34.021
subj. prob survive past 75	68.671	27.954	61.668	31.013
prob missing	0.016	0.124	0.039	0.193
NT	6170		6800	
N	1283		1440	

Notes: respondents working at baseline, age 51-56, HRS and Warbabies cohort

Table 3: Estimation Results – Females

Controls	full-time	part-time	trans. wlth	ss claim
lagged outcome				
lag full-time	3.25328***	1.63480***	0.64916	-2.06957***
	[23.03]	[12.20]	[1.09]	[-9.35]
lag part-time	1.97823***	2.92826***	0.27327	-1.39690***
	[12.98]	[22.48]	[0.43]	[-5.58]
lag trans. wealth	-0.00932***	-0.00615**	0.61311***	-0.00136
	[-3.30]	[-2.19]	[29.05]	[-0.33]
lag receive SSben	-0.3614	-0.1728	-1.77572*	
	[-1.58]	[-0.95]	[-1.89]	
initial conditions				
i. part-time	-0.55234***	0.54373***	-0.19061	-0.35623*
	[-4.36]	[4.76]	[-0.34]	[-1.80]
i. self-employed	-1.30577***	-1.24353***	0.07726	-0.24793
	[-6.56]	[-7.02]	[0.08]	[-0.78]
i. trans. wlth	0.00328	0.00839***	0.13973***	-0.0026
	[1.12]	[2.78]	[5.30]	[-0.65]
i. log pension wlth	-0.18016*	-0.11532	0.77635	0.01276
	[-1.72]	[-1.05]	[1.57]	[0.06]
age/10	0.1888	-0.30063	-1.59527	4.70842***
	[0.31]	[-0.49]	[-0.66]	[6.06]
age/10 sq	-0.93084***	-0.14006	2.27707*	
	[-2.76]	[-0.44]	[1.76]	
i. married	0.02889	-0.07719	-0.35716	0.21482
	[0.24]	[-0.57]	[-0.59]	[1.05]
i. widowed	0.01032	-0.07376	-1.06634	0.59863*
	[0.06]	[-0.36]	[-1.17]	[1.95]
i. other adults hh	0.20324**	0.09034	-0.58757	-0.20739
	[2.28]	[0.96]	[-1.33]	[-1.36]

i. severe hlt	0.09081	0.21284	-0.47906	0.03314
	[0.71]	[1.52]	[-0.69]	[0.15]
i. mild hlt	-0.20985***	-0.19300**	-1.27400***	0.2131
	[-2.76]	[-2.14]	[-3.01]	[1.50]
i. some iadl	0.22296	0.09652	-1.10513	-0.20786
	[1.24]	[0.62]	[-1.35]	[-0.66]
i. some adl	-0.19722	-0.77713***	0.64386	0.24426
	[-0.96]	[-2.72]	[0.54]	[0.71]
i. srh fair/poor	-0.75908***	-0.54481***	-1.13195	-0.12117
	[-4.82]	[-3.27]	[-1.33]	[-0.39]
black	0.05003	0.21583	-2.69964***	0.05079
	[0.39]	[1.57]	[-4.08]	[0.22]
hispanic	0.23682	0.05092	-3.35279***	-0.27654
	[1.32]	[0.22]	[-3.35]	[-0.86]
l.t. high school	-0.10493	-0.13177	-1.63678**	-0.2759
	[-0.72]	[-0.88]	[-2.34]	[-1.01]
college ed	0.17867	0.20798	0.69599	-0.24392
	[1.60]	[1.63]	[1.36]	[-1.19]
i. non-labor income	-0.00151	0.00099	0.08729***	-0.00346
	[-1.02]	[0.71]	[9.43]	[-1.36]
i. career occup.	-0.0638	0.08698	-1.08271**	0.27293
	[-0.60]	[0.73]	[-2.15]	[1.53]
i. professional	0.17029	-0.03085	0.95111*	-0.181
	[1.54]	[-0.24]	[1.73]	[-0.91]
i. blue-collar	-0.26436**	-0.11776	-0.49685	0.30456
	[-2.16]	[-0.89]	[-0.80]	[1.34]
i. quarters cov.	-0.00137	0.00111	-0.01176	0.01047**
	[-0.55]	[0.39]	[-0.93]	[2.16]
i. log aime	2.43377***	-0.65069	3.85838	-2.15302
	[2.64]	[-0.72]	[0.79]	[-0.90]
i. wage rate	-0.00882**	-0.00700**	-0.0025	-0.0076
	[-2.12]	[-2.15]	[-0.10]	[-0.74]
i. any pension	0.52694**	0.18699	-0.32585	0.0419
	[2.15]	[0.73]	[-0.28]	[0.09]
i. subj.prob.work62	0.00687***	0.00056	-0.01670**	-0.00667***
	[4.19]	[0.31]	[-2.13]	[-2.66]
i. subj.prob.work65	0.00321*	0.00222	-0.00895	-0.00591**
	[1.67]	[1.01]	[-0.95]	[-2.18]
i. subj.prob.live75	-0.00227	0.00153	-0.00477	-0.00029
	[-1.40]	[0.86]	[-0.57]	[-0.10]
i. prob missing	-0.64433	-0.4281	-1.85299	-1.00168
	[-1.49]	[-0.98]	[-1.18]	[-1.13]

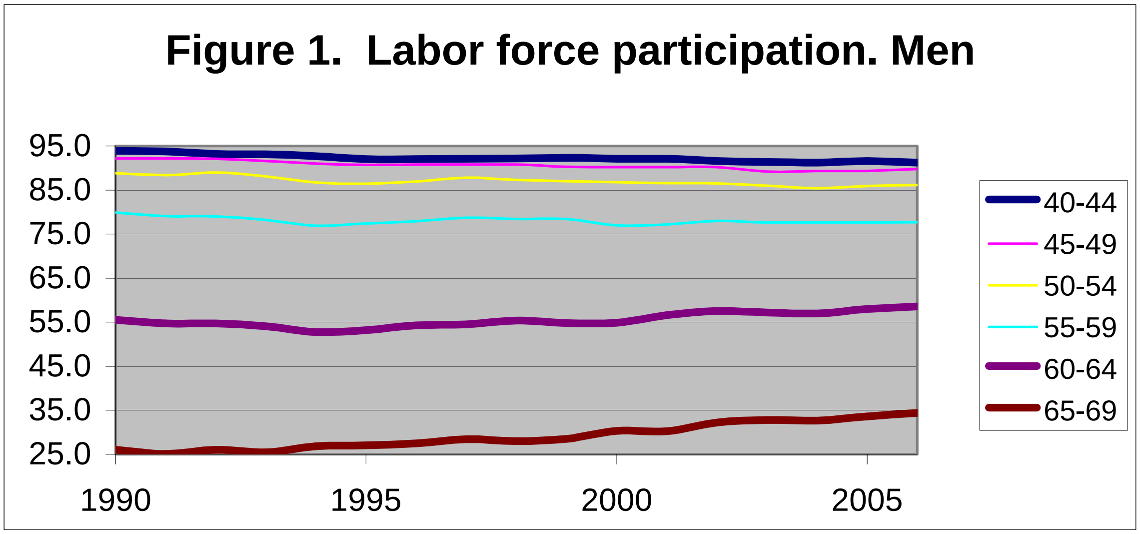
Notes: point estimates along with t-statistics based on panel robust standard errors, *** <0.01, ** <0.05, * <0.10

Table 4: Estimation Results – Males

Controls	full-time	part-time	trans. wlth	ss claim
lagged outcome				
lag full-time	2.60883***	1.15676***	1.12900*	-1.90997***
	[23.81]	[8.17]	[1.95]	[-10.52]
lag part-time	1.41089***	2.56245***	-0.6578	-1.11957***
	[8.93]	[16.91]	[-0.92]	[-4.34]
lag trans. wealth	-0.00847***	-0.00451	0.54837***	0.00188
	[-3.30]	[-1.39]	[23.01]	[0.51]
lag receive SSben	-0.53035***	-0.13776	-0.78712	
	[-2.82]	[-0.70]	[-0.97]	
initial conditions				
i. part-time	-0.38575***	0.64191***	1.47384**	0.38758*
	[-2.68]	[4.25]	[2.03]	[1.67]
i. self-employed	-1.02955***	-0.67833***	0.05835	-0.15297
	[-7.51]	[-4.07]	[0.08]	[-0.68]
i. trans. wlth	0.00202	0.00413	0.19333***	-0.0026
	[0.84]	[1.24]	[7.59]	[-0.73]
i. log pension wlth	-0.21917***	0.04374	1.00618***	0.35971***
	[-3.03]	[0.46]	[2.93]	[2.76]
age/10	-0.82669	-0.174	2.76771	5.97727***
	[-1.49]	[-0.25]	[1.17]	[8.77]
age/10 sq	-0.4501	0.02807	1.1377	
	[-1.51]	[0.08]	[0.93]	
i. married	0.30576**	0.22676	0.95748	0.11253
	[2.56]	[1.22]	[1.44]	[0.51]
i. widowed	-0.09638	-0.03524	-2.31054	2.63885***
	[-0.29]	[-0.08]	[-1.30]	[3.43]
i. other adults hh	0.0408	0.01997	-0.4418	-0.13514
	[0.55]	[0.19]	[-1.09]	[-0.97]

i. severe hlt	-0.14116	-0.28910*	-0.7671	0.00883
	[-1.39]	[-1.83]	[-1.33]	[0.04]
i. mild hlt	-0.09004	-0.05958	-0.68700*	-0.09531
	[-1.33]	[-0.63]	[-1.88]	[-0.69]
i. some iadl	0.1386	0.13947	-0.80109	-0.10549
	[0.75]	[0.56]	[-0.92]	[-0.39]
i. some adl	-0.17996	-0.81376**	-2.32868*	-0.22171
	[-0.75]	[-2.17]	[-1.79]	[-0.50]
i. srh fair/poor	-0.35146**	-0.01868	-1.63467**	0.52869**
	[-2.55]	[-0.10]	[-2.13]	[2.07]
black	-0.0032	-0.09819	-3.28271***	0.0751
	[-0.02]	[-0.52]	[-4.42]	[0.28]
hispanic	-0.15304	-0.34647	-2.77280***	-0.0878
	[-1.07]	[-1.61]	[-2.93]	[-0.32]
l.t. high school	-0.08488	-0.1307	-1.85977***	-0.04964
	[-0.70]	[-0.75]	[-2.60]	[-0.21]
college ed	0.23080**	0.28027**	0.80724	-0.2346
	[2.38]	[1.99]	[1.48]	[-1.32]
i. non-labor income	0.00147	0.00152	0.06762***	-0.01006***
	[1.31]	[1.06]	[8.18]	[-4.20]
i. career occup.	0.00229	-0.08584	-0.23172	-0.29484*
	[0.02]	[-0.70]	[-0.45]	[-1.81]
i. professional	0.08596	0.20266	1.85221***	-0.62205***
	[0.80]	[1.33]	[3.16]	[-3.24]
i. blue-collar	0.01404	0.02554	0.01611	0.08062
	[0.15]	[0.18]	[0.03]	[0.42]
i. quarters cov.	-0.00045	0.00820**	-0.01987	0.00984**
	[-0.18]	[2.35]	[-1.35]	[1.98]
i. log aime	1.34329	-3.77934***	18.77222***	0.17728
	[1.31]	[-2.81]	[3.07]	[0.07]
i. wage rate	0.0007	-0.00215	-0.00686	-0.00573**
	[0.32]	[-0.93]	[-0.56]	[-2.07]
i. any pension	0.63094***	-0.02524	0.61788	-0.37856
	[3.22]	[-0.10]	[0.65]	[-1.13]
i. subj.prob.work62	0.00822***	-0.00454**	-0.01983***	-0.01397***
	[6.59]	[-2.20]	[-2.91]	[-5.12]
i. subj.prob.work65	0.00222	0.00630***	-0.00547	0.00244
	[1.45]	[2.71]	[-0.68]	[0.87]
i. subj.prob.live75	0.00009	0.00013	0.0057	0.00087
	[0.07]	[0.07]	[0.74]	[0.32]
i. prob missing	-0.21188	-0.21373	-0.5083	-0.41073
	[-0.91]	[-0.74]	[-0.39]	[-0.97]

Notes: point estimates along with t-statistics based on panel robust standard errors, *** <0.01, ** <0.05, * <0.10



Source: CPS data.

Figure 2: Simulated and Actual Full-Time Work in 1931-1941 Cohort

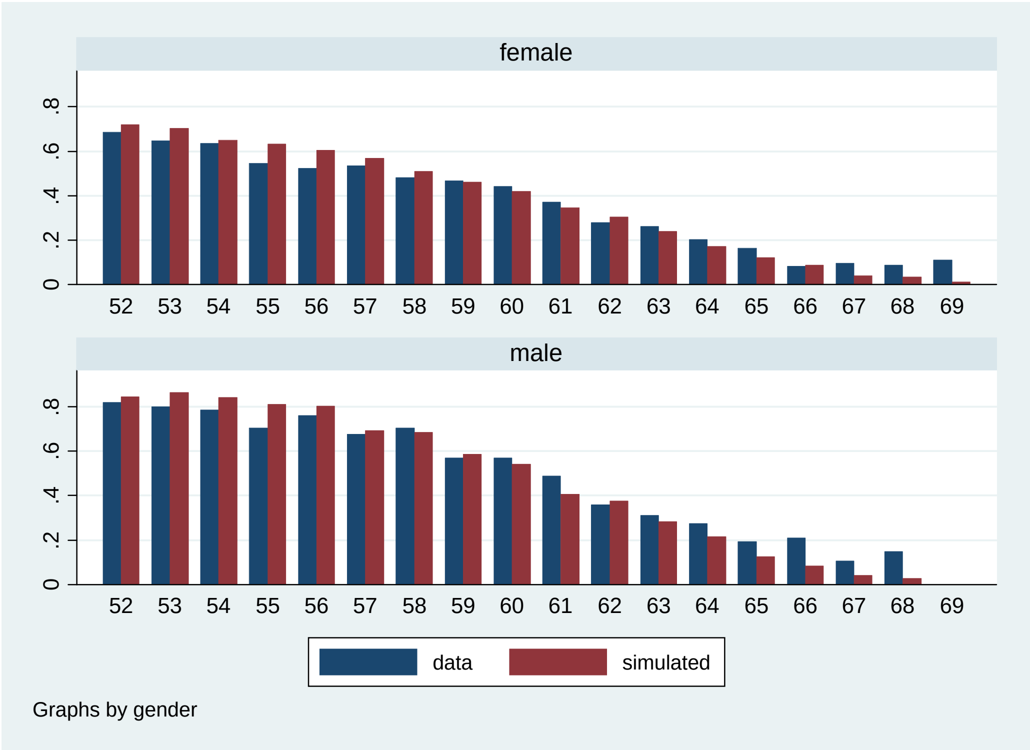


Figure 3: Simulated and Actual Social Security Benefit Receipt Among 1931-1941 Cohort

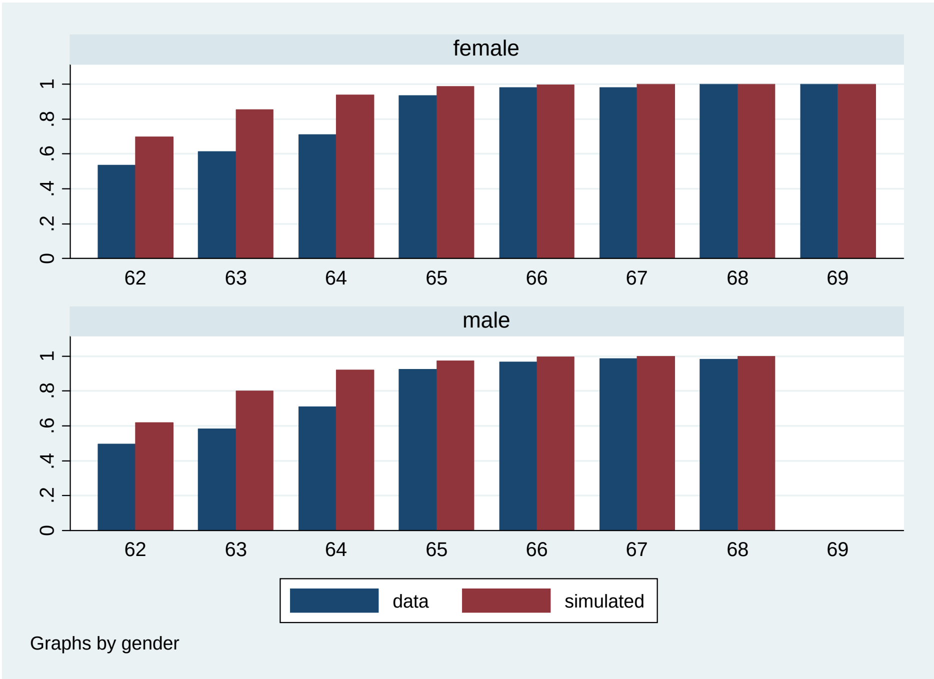


Figure 4 :Simulated and Actual Median Household Wealth in 1931-1941 Cohort

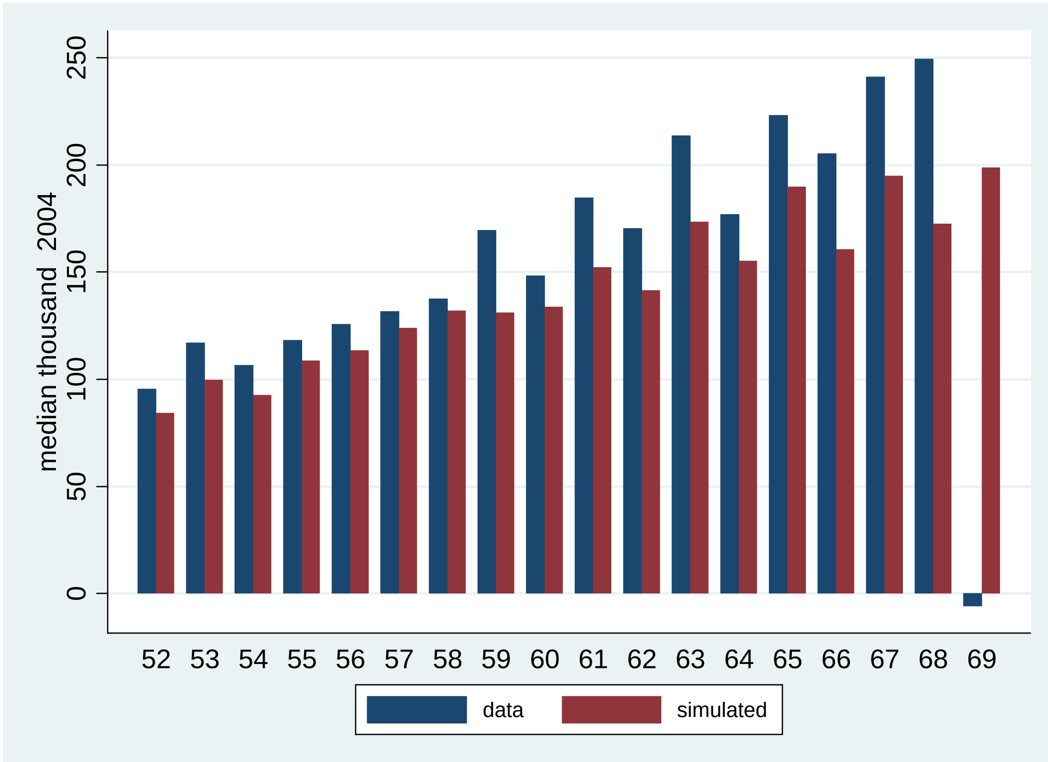


Figure 5: Forecasts of Labor Force Status for Early Baby Boomers

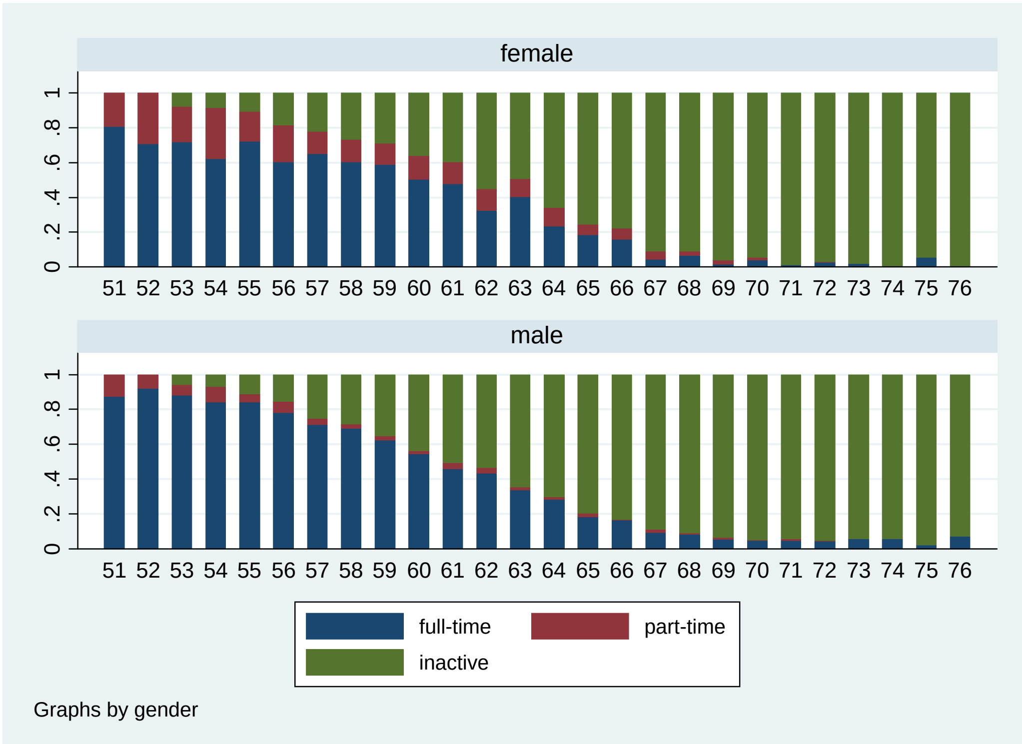


Figure 6: Forecasted Social Security Benefit Receipt for Early Boomers

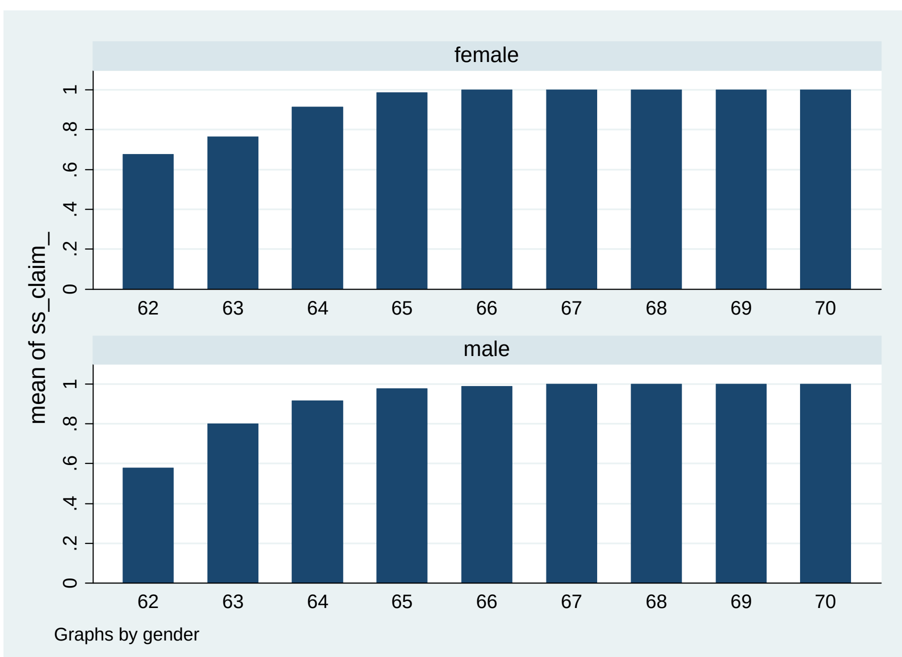


Figure 7: Comparison of Simulated Full-time work for 1931-1941 and Early Boomer Cohorts

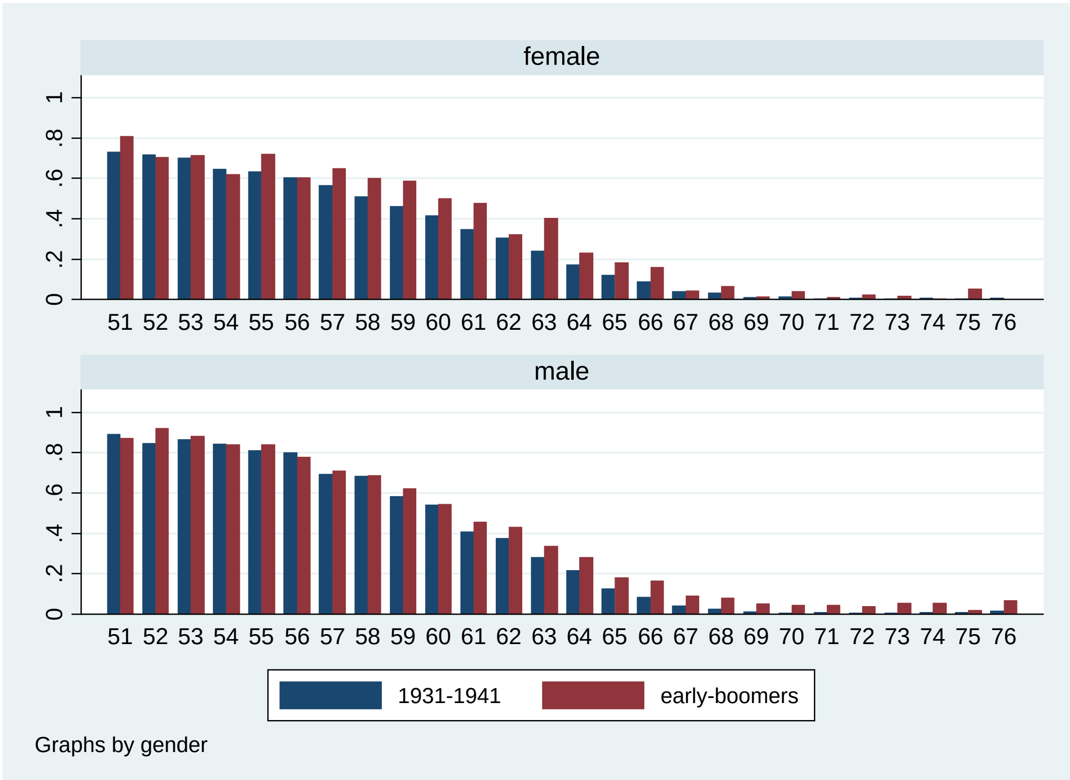
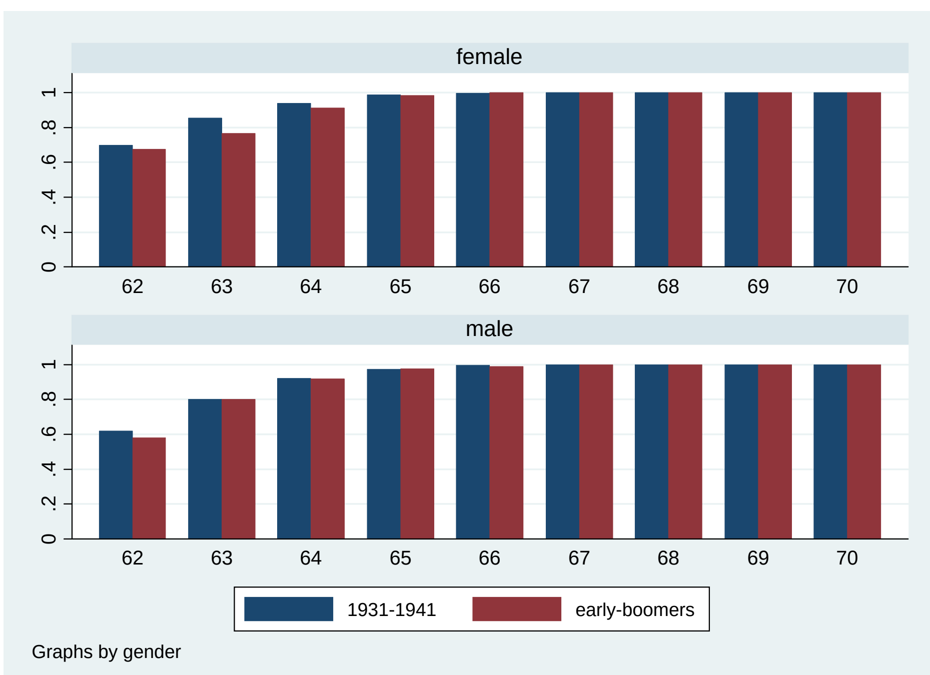


Figure 8: Comparison of Simulated Social Security Benefits for 1931-1941 and Early Boomers Cohort



Appendix 1:

Estimating pension entitlements relating outcomes to baseline pension reports

Estimating pension entitlements from self-reports has been deemed difficult due to the large number of survey items involved, item-nonresponse affecting each one of them and the more general concern that workers do not actually know much about their pensions. (Mitchell, 1988) and Gustman and Steinmeier (2005). Administrative data on the other hand have the shortcoming that they tend to be available only for a sub-sample of a survey raising the potential for biased results due to selection. Here we use an alternative approach that relies exclusively on self-reported pension information, but allows for measurement error along a number of dimensions, including whether the person is covered by a pension in the first place, but also plan type.

The starting point of this approach is that the individual will have most accurate knowledge about his or her pension arrangements on a job (pension type and pension value) at the time of job separation. At this time the person either starts receiving a pension or has to make some real world decisions about how the funds will be handled (cash out, roll-over into IRA, partial lump-sum, accumulate with employer etc.). In the next HRS survey wave following this event, the respondents are asked for a full inventory of pensions on the job that the person just recently quit, including number of pensions, respective pension type, disposition of that pension and the associated amounts.

<u>Method:</u>

We estimate the probability of pension receipts (any receipts and the associated amounts) as a function of self-reported characteristics at baseline. We estimate this relationship for the HRS cohort which was first interviewed in 1992 at age 51-61 and who has since been interviewed a total of eight times over a period of 14 years. The vast majority of these initial respondents has retired by the time of the last interview (2006) or quit the employer they were working for back in 1992. By 2006 they have reached age 65 to 75. For each worker in 1992 we follow them over time in the HRS survey and find the time when they leave their employer from 1992 and observe the inventory of pensions.

More specifically:

Take the sample of all workers (Rs reporting a current job) at baseline (i.e. 1992). Include also those workers who report not being included in a pension plan at the time of interview as these workers may well become eligible for inclusion in a pension plan over time (or realize that they actually had been included).

Follow all these workers over time and find when they leave the job they held in 1992. At that point HRS takes another inventory of Rs pensions and in particular what these pensions are worth at the time of job separation. Labeling what Rs get from their pension(s) at this point as "pension extractions" we distinguish five types of extractions that are identified in the survey at job separation:

- DC extractions
- DB extractions – current lump sum
- DB extractions – current flow
- DB extractions – future flow
- DB extractions – future lump sum

Estimate probability of extraction:

For the sample of all workers we estimate the probability of an extraction (using a logit specification); we perform a separate estimation for each type of extraction (i.e. 5 equations) as a function of covariates (covered by union, any pension, number of pensions, any DB, any DC, any DK type, a reduced set of industry and occupation dummies, sex, education, and age). The set of industry and occupation dummies differs slightly across the different extractions equations to maximize predictive power (and reduce noise in predictions).

Estimate amounts conditional on extractions:

conditional on having an extraction of a particular type, we estimate the associated amount as a function of covariates (tenure on current job, any DB, any

DC, any type DK, sex, union, education, age, earnings on current job, current DC balance (1st through 3rd plan), expected DB benefit amounts (1st through 3rd plan).

The total present value of expected pension wealth for a worker is defined by

$$PV_t(PW) = \sum_i P\left(extraction_i\right) \cdot E(PV_i \mid extraction_i)$$

where $i = 1 \ldots 5$ denotes the five types of different pension extractions listed above.

Note that amounts (extractions and amounts reported at baseline) are adjusted to be comparable across the type of pensions and the types of extractions. This involves:

- present value calculations for benefit flows (taking into account probabilities of survival); this is to achieve comparability of DB flows to stock measures like DC balances

- discounting so that amounts measured at different points in time are comparable; discounting also captures the respondent's distance to claiming the respective benefits (e.g. benefits expected in the far future versus those expected in the near future.)

Interpretation of the resulting estimates of pension entitlements:

This approach is equivalent to estimating the probability of extractions for each single period and then multiplying by the associated amounts conditional on receipt, and integrating over all future periods. The resulting pension wealth measure is forward-looking in that it does not give the value of pension entitlements if the worker were to quit in the current period, but instead the expected present value of future pension receipts for the group of workers with similar characteristics and pensions. It varies from time period to time period as a function of the worker's reported characteristics which is mainly by age; but also when the individual changes his or her reports about pension characteristics.