The Future Elderly Model: Technical Documentation

Dana P. Goldman, University of Southern California
Darius Lakdawalla, University of Southern California
Pierre-Carl Michaud, RAND Corporation
Christine Eibner, RAND Corporation
Yuhui Zheng, National Bureau of Economic Research
Adam Gailey, RAND Corporation
Igor Vaynman, RAND Corporation
Jeffrey Sullivan, Precision Health Economics, LLC
Bryan Tysinger, University of Southern California
Duncan Ermini Leaf, University of Southern California

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1.1 Background

The Future Elderly Model (FEM) is a microsimulation model originally developed out of an effort to examine health and health care costs among the elderly Medicare population (age 65+). A description of the previous incarnation of the model can be found in Goldman et al. (2004). The original work was founded by the Centers for Medicare and Medicaid Services and carried out by a team of researchers composed of Dana P. Goldman, Paul G. Shekelle, Jayanta Bhattacharya, Michael Hurd, Geoffrey F. Joyce, Darius N. Lakdawalla, Dawn H. Matsui, Sydne J. Newberry, Constantijn W. A. Panis and Baoping Shang.

Since then various extensions have been implemented to the original model. The most recent version now projects health outcomes for all Americans aged 51 and older and uses the Health and Retirement Study (HRS) as a host dataset rather than the Medicare Current Beneficiary Survey (MCBS). The work has also been extended to include economic outcomes such as earnings, labor force participation and pensions. This work was funded by the National Institute on Aging through its support of the RAND Roybal Center for Health Policy Simulation (P30AG024968), the Department of Labor through contract J-9-P-2-0033, the National Institutes of Aging through the R01 grant "Integrated Retirement Modeling" (R01AG030824) and the MacArthur Foundation Research Network on an Aging Society. Finally, the computer code of the model was transferred from Stata to C++. This report incorporates these new development efforts in the description of the model.

1.2 Overview

The defining characteristic of the model is the modeling of real rather than synthetic cohorts, all of whom are followed at the individual level. This allows for more heterogeneity in behavior than would be allowed by a cell-based approach. Also, since the HRS interviews both respondent and spouse, we can link records to calculate household-level outcomes such as net income and Social Security retirement benefits, which depend on the outcomes of both spouses. The omission of the population younger than age 51 sacrifices little generality, since the bulk of expenditure on the public programs we consider occurs after age 50. However, we may fail to capture behavioral responses among the young.

The model has three core components:

- The initial cohort module predicts the economic and health outcomes of new cohorts of 51/52 year-olds. This module takes in data from the Health and Retirement Study (HRS) and trends calculated from other sources. It allows us to "generate" cohorts as the simulation proceeds, so that we can measure outcomes for the age 51+ population in any given year.

- The transition module calculates the probabilities of transiting across various health states and financial outcomes. The module takes as inputs risk factors such as smoking, weight, age and education, along with lagged health and financial states. This allows for a great deal of heterogeneity and fairly general feedback effects. The transition probabilities are estimated from the longitudinal data in the Health and Retirement Study (HRS).

- The policy outcomes module aggregates projections of individual-level outcomes into policy outcomes such as taxes, medical care costs, pension benefits paid, and disability benefits. This component takes account of public and private program rules to the extent allowed by the available outcomes. Because we have access to HRS-linked restricted data from Social Security records and employer pension plans, we are able to realistically model retirement benefit receipt.

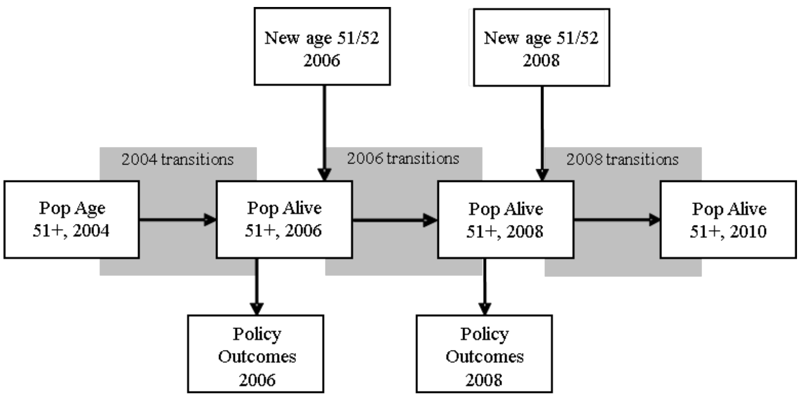

Figure 1: Architecture of the FEM

Figure 1 provides a schematic overview of the model. We start in 2004 with an initial population aged 51+ taken from the HRS. We then predict outcomes using our estimated transition probabilities (see section 4.1). Those who survive make it to the end of that year, at which point we calculate policy outcomes for the year. We then move to the following time period (two years later), when a new cohort of 51 and 52 year-olds enters (see section 5.1). This entrance forms the new age 51+ population, which then proceeds through the transition model as before. This process is repeated until we reach the final year of the simulation.

1.3 Comparison with other prominent microsimulation models of health expenditures

The FEM is unique among existing models that make health expenditure projections. It is the only model that projects health trends rather than health expenditures. It is also the only model that generates mortality out of assumptions on health trends rather than historical time series.

1.3.1 CBOLT Model

The Congressional Budget Office (CBO) uses time-series techniques to project health expenditure growth in the short term and then makes an assumption on long-term growth. They use a long term growth of excess costs of 2.3 percentage points starting in 2020 for Medicare. They then assume a reduction in excess cost growth in Medicare of 1.5% through 2083, leaving a rate of 0.9% in 2083. For non-Medicare spending they assume an annual decline of 4.5%, leading to an excess growth rate in 2083 of 0.1%.

1.3.2 Centers for Medicare and Medicaid Services

The Centers for Medicare and Medicaid Services (CMS) performs an extrapolation of medical expenditures over the first ten years, then computes a general equilibrium model for years 25 through 75 and linearly interpolates to identify medical expenditures in years 11 through 24 of their estimation. The core assumption they use is that excess growth of health expenditures will be one percentage point higher per year for years 25-75 (that is if nominal GDP growth is 4%, health care expenditure growth will be 5%).

2 Data sources used for estimation

The Health and Retirement Study is the main data source for the model. We supplemented this data with merged Social Security covered earnings histories and data on health trends and health care costs coming from 3 major health surveys in the U.S. We describe these surveys below and the samples we selected for the analysis. We first list the variables used in the analysis. We then give details on the data sources.

Estimated Outcomes in Initial Conditions Model

Economic Outcomes	**Health Outcomes**
Employment	Hypertension
Earnings	Heart Disease
Wealth	Self-Reported Health
Defined Contribution Pension Wealth	BMI Status
Pension Plan Type	Smoking Status
AIME	Functional Status
Social Security Quarters of Coverage	
Health Insurance	

Estimated Outcomes in/from Transition Model

Economic Outcomes	**Health Outcomes**	**Other Outcomes**
Employment	Death	Income Tax Revenue
Earnings	Heart	Social Security Revenue
Wealth	Stroke	Medicare Revenue
Demographics	Cancer	Medical Expenses
Health Insurance	Hypertension	Medicare Part A Expenses
Disability Insurance Claim	Diabetes	Medicare Part B Expenses
Defined Benefit Claim	Lung Disease	Medicare Part B Enrollment
SSI Claim	Nursing Home	Medicare Part D Enrollment
Social Security Claim	BMI	OASI Enrollment
	Smoking Status	DI enrollment
	ADL Limitations	SSI enrollment
	IADL Limitations	Medicaid Enrollment
		Medicaid Expenditures

2.1 Health and Retirement Study

The Health and Retirement Study (HRS) waves 2000-2008 are used to estimate the transition model. Interviews occur every two years. We use the dataset created by RAND (RAND HRS, version K) as our basis for the analysis. We use all cohorts in the analysis and consider sampling weights whenever appropriate. When appropriately weighted, the HRS in 2004 is representative of U.S. households where at least one member is at least 51. The HRS is also used as the host data for the simulation (pop 51+ in 2004) and for new cohorts (aged 51 and 52 in 2004).

The HRS adds new cohorts every six years. Until recently, the latest available cohort had been added in 2004, which is why that is the FEM's base year. The FEM is currently being updated to use the newly released 2010 data.

2.2 Social Security covered earnings files

To get information on Social Security entitlements of respondents, we match the HRS data to the Social Security Covered Earnings files of 1992, 1993, 1998, 2004 and 2006 which provides information on earning histories of respondents as well as their entitlement to future Social Security benefits. We then construct the average indexed monthly earnings (AIME), the basis for the determination of benefit levels, from these earning histories. The AIME is constructed by first indexing using the National Wage Index (NWI) to the wage level when the respondent turns age 60. If this occurs after 2008, we project the evolution of the NWI using the average annual rate of change of the last 20 years (2.9% nominal). We then take the 35 highest years (if less than 35 years are available, remaining years are considered zero earning years) and take the average. We then convert back this annual amount on a monthly basis and convert back to $2004 U.S. dollars using the CPI. Quarters of coverage, which determine eligibility to Social Security, are defined as the sum of posted quarters to the file. A worker is eligible for Social Security if he has accumulated at least 40 quarters of coverage. A worker roughly accumulates a quarter of coverage for every $4000 of coverage earnings up to a maximum of 4 per year. Not all respondents agree to have their record matched. Hence, there is the potential for non-representativeness. However, recent studies show that the extent of non-representativeness is quite small and that appropriate weighting using HRS weights mostly corrects for this problem (Kapteyn et al., 2006).

2.3 National Health Interview Survey

The National Health Interview Survey (NHIS) contains individual-level data on height, weight, smoking status, self-reported chronic conditions, income, education, and demographic variables. It is a repeated cross-section done every year for several decades. But the survey design has been significantly modified several times. Before year 1997, different subgroups of individuals were asked about different sets of chronic conditions, after year 1997, a selected sub-sample of the adults were asked a complete set of chronic conditions. The survey questions are quite similar to that in HRS. As a result, for projecting the trends of chronic conditions for future 51/52 year-olds, we only use data from 1997 to 2010. A review of survey questions is provided in Table 2. Information on weight and height were asked every year, while information on smoking was asked in selected years before year 1997, and has been asked annually since year 1997.

FEM uses NHIS to project prevalence of chronic conditions in future cohorts of 51-52 year olds. The method is discussed in Sections 3.1 and 5.1. FEM also relies on the Medical Expenditure Panel Survey, a subsample of NHIS respondents, for model estimation. See section 2.4 for a description.

2.4 Medical Expenditure Panel Survey

The Medical Expenditure Panel Survey (MEPS), beginning in 1996, is a set of large-scale surveys of families and individuals, their medical providers (doctors, hospitals, pharmacies, etc.), and employers across the United States. The Household Component (HC) of the MEPS provides data from individual households and their members, which is supplemented by data from their medical providers. The Household Component collects data from a representative sub sample of households drawn from the previous year's National Health Interview Survey (NHIS). Since NHIS does not include the institutionalized population, neither does MEPS: this implies that we can only use the MEPS to estimate medical costs for the non-elderly population. Information collected during household interviews include: demographic characteristics, health conditions, health status, use of medical services, sources of medical payments, and body weight and height. Each year the household survey includes approximately 12,000 households or 34,000 individuals. Sample size for those aged 51-64 is about 4,500. MEPS has comparable measures of social-economic (SES) variables as those in HRS, including age, race/ethnicity, educational level, census region, and marital status.

FEM uses MEPS years 2000-2010 for cost estimation. See Section 6.4 for a description. FEM also uses MEPS 2001 data for QALY model estimation. This is described in Section 4.3.

2.5 Medicare Current Beneficiary Survey

The Medicare Current Beneficiary Survey (MCBS) is a nationally representative sample of aged, disabled and institutionalized Medicare beneficiaries. The MCBS attempts to interview each respondent twelve times over three years, regardless of whether he or she resides in the community, a facility, or transitions between community and facility settings. The disabled (under 65 years of age) and oldest-old (85 years of age or older) are over-sampled. The first round of interviewing was conducted in 1991. Originally, the survey was a longitudinal sample with periodic supplements and indefinite periods of participation. In 1994, the MCBS switched to a rotating panel design with limited periods of participation. Each fall a new panel is introduced, with a target sample size of 12,000 respondents and each summer a panel is retired. Institutionalized respondents are interviewed by proxy. The MCBS contains comprehensive self-reported information on the health status, health care use and expenditures, health insurance coverage, and socioeconomic and demographic characteristics of the entire spectrum of Medicare beneficiaries. Medicare claims data for beneficiaries enrolled in fee-for-service plans are also used to provide more accurate information on health care use and expenditures. MCBS years 1992-2010 are used for estimating medical cost and enrollment models. See section 6.4 for discussion.

3 Data sources for trends and baseline scenario

Two types of trends need to be projected in the model. First, we need to project trends in the incoming cohorts (the future new age 51/52 individuals). This includes trends in health and economic outcomes. Second, we need to project excess aggregate growth in real income and excess growth in health spending.

3.1 Data for trends in entering cohorts

We used a multitude of data sources to compute U.S. trends. First, we used NHIS for chronic conditions and applied the methodology discussed in (Goldman et al., 2004). The method consists of projecting the experience of younger cohorts into the future until they reach age 51. The projection method is tailored to the synthetic cohorts observed in NHIS. For example, we observe a representative sample of age 35 individuals born in 1945 in 1980. We follow their disease patterns in 1980 to 1981 surveys by then selecting those aged 36 in 1981, accounting for mortality, etc.

We then collected information on other trends, i.e. for obesity and smoking, from other studies (Honeycutt et al., 2003; Levy, 2006; Poterba et al., 2009; Ruhm, 2007; Mainous III et al., 2007). Table 3 presents the sources and Table 4 presents the trends we use in the baseline scenario. Table 5 presents the prevalence of obesity, hypertension, diabetes, and current smokers in 1978 and 2004, and the annual rates of change from 1978 to 2004. We refer the readers to the analysis in Goldman et al. (2004) for information on how the trends were constructed.

3.2 Data for other projections

We make two assumptions relating to real growth in wages and medical costs. Firstly, as is done in the 2009 Social Security Trustees report intermediate cost scenario, we assume a long term real increase in wages (earnings) of 1.1% per year. Next, following the Centers for Medicare and Medicaid Services, we assume excess real growth in medical costs (that is additional cost growth to GDP growth), as 1.5% in 2004, reducing linearly to 1% in 2033, .4% in 2053, and -.2% in 2083. We also include the Affordable Care Act cost growth targets as an optional cap on medical cost growth. Baseline medical spending figures presented assume those targets are met.

GDP growth in the near term (through 2019) is based on CBO projections, with the OASDI Trustees assumption of 2% yearly afterwards.

3.3 Demographic adjustments

We make two adjustments to the weighting in the HRS to match population counts. Since we deleted some cases from the data and only considered the set of respondents with matched Social Security records, this takes account of selectivity based on these characteristics. First, we post-stratify the HRS sample by 5 year age groups, gender and race and rebalance weights using the Census Bureau 2000-2010 Intercensal Population Estimates. We do this for both the host data set and the new cohorts. We scale the weights for future new cohorts using 2012 National Population Projections based on race and gender. Second, we post- stratify the HRS sample of deaths between the 2002 and 2004 interview waves by 5 year age groups, gender and race and rebalance weights based on the Human Mortality Database.

Once the simulation begins, trends in migration and mortality are applied. We use net migration from the SSA Trustees report intermediate cost scenario. Seperate mortality rate adjustment factors are defined for the under and over 65 age groups based on the mortality projections from the 2013 SSA Trustees report. The SSA projections are interpolated through 2090, then extended using GLM with log link through 2150.

4 Estimation

In this section we describe the approach used to estimate the transition model, the core of the FEM, and the initial cohort model which is used to rejuvenate the simulation population.

4.1 Transition model

We consider a large set of outcomes for which we model transitions. Table 6 gives the set of outcomes considered for the transition model along with descriptive statistics and the population at risk when estimating the relationships.

Since we have a stock sample from the age 51+ population, each respondent goes through an individual-specific series of intervals. Hence, we have an unbalanced panel over the age range starting from 51 years old. Denote by j_{i0} the first age at which respondent i is observed and j_{iT_i} the last age when he is observed. Hence we observe outcomes at ages $j_i = j_{i0}, \dots, j_{iT_i}$.

We first start with discrete outcomes which are absorbing states (e.g. disease diagnostic, mortality, benefit claiming). Record as $h_{i,j_i,m} = 1$ if the individual outcome m has occurred as of age j_i. We assume the individual-specific component of the hazard can be decomposed in a time invariant and variant part. The time invariant part is composed of the effect of observed characteristics x_i that are constant over the entire life course and initial conditions $h_{i,j_0,-m}$ (outcomes other than the outcome m) that are determined before the first age in which each individual is observed [1]. The time-varying part is the effect of previously diagnosed outcomes $h_{i,j_i-1,-m}$, on the hazard for m.[2] We assume an index of the form $z_{m,j_i} = x_i\beta_m + h_{i,j_i-1,-m}\gamma_m + h_{i,j_0,-m}\psi_m$. Hence, the latent component of the hazard is modeled as

$$h^*_{i,j_i,m} = x_i\beta_m + h_{i,j_i-1,-m}\gamma_m + h_{i,j_0,-m}\psi_m + a_{m,j_i} + \varepsilon_{i,j_i,m}, \tag{1}$$

$$m = 1, \dots, M_0,\ j_i = j_{i0}, \dots, j_{i,T_i},\ i = 1, \dots, N$$

[1] Section 9.1 explains why the $h_{i,j_0,-m}$ terms are included.

[2] With some abuse of notation, $j_i - 1$ denotes the previous age at which the respondent was observed.

The term $\varepsilon_{i,j_i,m}$ is a time-varying shock specific to age j_i. We assume that this last shock is normally distributed and uncorrelated across diseases. We approximate a_{m,j_i} with an age spline. After several specification checks, knots at age 65 and 75 appear to provide the best fit. This simplification is made for computational reasons since the joint estimation with unrestricted age fixed effects for each condition would imply a large number of parameters. The absorbing outcome, conditional on being at risk, is defined as

$$h_{i,j_i,m} = \max\{I(h^*_{i,j_i,m} > 0), h_{i,j_i-1,m}\}$$

The occurrence of mortality censors observation of other outcomes in a current year. Mortality is recorded from exit interviews.

A number of restrictions are placed on the way feedback is allowed in the model. Table 7 documents restrictions placed on the transition model. We also include a set of other controls. A list of such controls is given in Table 8 along with descriptive statistics.

We have three other types of outcomes:

1. First, we have binary outcomes which are not an absorbing state, such as living in a nursing home. We specify latent indices as in (1) for these outcomes as well but where the lag dependent outcome also appears as a right-hand side variable. This allows for state-dependence.
2. Second, we have ordered outcomes. These outcomes are also modeled as in (1) recognizing the observation rule is a function of unknown thresholds ς_m. Similarly to binary outcomes, we allow for state-dependence by including the lagged outcome on the right-hand side.
3. The third type of outcomes we consider are censored outcomes, earnings and financial wealth. Earnings are only observed when individuals work. For wealth, there are a non-negligible number of observations with zero and negative wealth. For these, we consider two part models where the latent variable is specified as in (1) but model probabilities only when censoring does not occur. In total, we have M outcomes.

The parameters $\theta_1 = \left(\{\beta_m, \gamma_m, \psi_m, \varsigma_m\}_{m=1}^{M},\right)$, can be estimated by maximum likelihood. Given the normality distribution assumption on the time-varying unobservable, the joint probability of all time-intervals until failure, right-censoring or death conditional on the initial conditions $h_{i,j_0,-m}$ is the product of normal univariate probabilities. Since these sequences, conditional on initial conditions, are also independent across diseases, the joint probability over all disease-specific sequences is simply the product of those probabilities.

For a given respondent observed from initial age j_{i0} to a last age j_{T_i}, the probability of the observed health history is (omitting the conditioning on covariates for notational simplicity)

$$l_i^{-0}(\theta; h_{i,j_{i0}}) = \left[\prod_{m=1}^{M-1} \prod_{j=j_{i1}}^{j_{T_i}} P_{ij,m}(\theta)^{(1-h_{ij-1,m})(1-h_{ij,M})}\right] \times \left[\prod_{j=j_{i1}}^{j_{T_i}} P_{ij,M}(\theta)\right]$$

We use the -0 superscript to make explicit the conditioning on $\mathbf{h}_{i,j_{i0}} = (h_{i,j_{i0},0}, \ldots, h_{i,j_{i0},M})'$. We have limited information on outcomes prior to this age. The likelihood is a product of M terms with the mth term containing only $(\beta_m, \gamma_m, \psi_m, \varsigma_m)$. This allows the estimation to be done seperately for each outcome.

4.1.1 Inverse Hyperbolic Sine Transformation

One problem fitting the wealth and earnings distribution is that they have a long right tail and wealth has some negative values. We use a generalization of the inverse hyperbolic sine transform

(IHT) presented in MacKinnon and Magee (1990). First denote the variable of interest y. The hyperbolic sine transform is

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

The inverse of the hyperbolic sine transform is

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

Consider the inverse transformation. We can generalize such transformation, first allowing for a shape parameter θ,

$$r(y) = h(\theta y)/\theta \tag{3}$$

Such that we can specify the regression model as

$$r(y) = x\beta + \varepsilon, \varepsilon \sim \mathrm{N}(0, \sigma^2) \tag{4}$$

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

$$g(y) = \frac{h(\theta(y + \omega)) - h(\theta\omega)}{\theta h'(\theta\omega)} \tag{5}$$

where $h'(a) = (1 + a^2)^{-1/2}$.

We specify (4) in terms of the transformation g. The shape parameters can be estimated from the concentrated likelihood for θ, ω. We can then retrieve β, σ by standard OLS.

Upon estimation, we can simulate

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

where η is a standard normal draw. Given this draw, we can retransform using (5) and (2)

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

4.2 Goodness-of-fit

To judge the goodness-of-fit of the model, we estimated parameters on the 1998-2008 estimation sample and simulated outcomes of 1998 HRS respondents up to 2008. We then compared simulated and actual outcomes in 1998, 2004 and 2008. Table 9 presents the results. Some differences exist but in general the fit is satisfactory.

4.3 Quality adjusted life years

As an alternative measure of life expectancy, we compute a quality adjusted life year (QALY) based on the EQ-5D instrument, a widely-used health-related quality-of-life (HRQoL) measure[3]. The scoring system for EQ-5D was first developed by Dolan (1997) using a UK sample. Later, a scoring system based on a US sample was generated (Shaw et al., 2005). The HRS does not ask the appropriate questions for computing EQ-5D, but the MEPS does. We use a crosswalk from MEPS to compute EQ-5D scores for HRS respondents not living in a nursing home[4].

The FEM has a more limited specification of functional status than what is available in the HRS. In order to predict HRQoL for the FEM simulation sample, we needed to build a

[3] Section 9.2.1 gives some background on HRQoL measures.

[4] Section 9.2.2 describes EQ-5D in MEPS. Details of the crosswalk model development are given in 9.2.3.

bridge between the FEM-type functional status and the predicted EQ-5D score in HRS. We used ordinary least squares to model the EQ-5D score predicted for non-nursing home in the 1998 HRS as a function of the six chronic conditions and the FEM-specification of functional status, The results are shown in Table 13.

The EQ-5D scoring method is based on a community population. Following a suggestion by Emmett Keeler, if a person is living in a nursing home, the QALY is reduced by 10%. We used the parameter estimates in Table 13 to predict EQ-5D scores for the entire FEM simulation sample and reduced nursing home residents' score by 10%. The resulting scores are representative of the U.S population (both in community and in nursing homes) ages 51 and over. Table 14 summarizes the EQ-5D score using this model for the stock FEM simulation sample in 2004.

5 Model for new cohorts

We first discuss the empirical strategy, then present the model and estimation results. The model for new cohorts integrates information coming from trends among younger cohorts with the joint distribution of outcomes in the current population of age 51 respondents in the HRS.

5.1 Information available and empirical strategy

For the transition model, we need to first to obtain outcomes listed in Table 15. Ideally, we need information on

$$f_t(y_{i1}, \ldots, y_{iM}) = f_t(\mathbf{y}_i)$$

where t denotes calendar time, and $\mathbf{y}_i = (y_{i1}, \ldots, y_{iM})$ is a vector of outcomes of interest whose probability distribution at time t is $f_t()$. Information on how the joint distribution evolves over time is not available. Trends in conditional distributions are rarely reported either.

Generally, we have (from published or unpublished sources) good information on trends for some moments of each outcome (say a mean or a fraction). That is, we have information on $g_{t,m}(y_{im})$, where $g_{t,m}()$ denotes the marginal probability distribution of outcome m at time t.

For example, we know from the NHIS repeated cross-sections that the fraction obese is increasing by roughly 2% a year among 51 year olds. In statistical jargon this means we have information on how the mean of the marginal distribution of y_{im}, an indicator variable that denotes whether someone is obese, is evolving over time.

We also have information on the joint distribution at one point in time, say year t_0. For example, we can estimate the joint distribution on age 51 respondents in the 1992 wave of the HRS, $f_{t_0}(\mathbf{y}_i)$.

We make the assumption that only some part of $f_t(\mathbf{y}_i)$ evolves over time. In particular, we will model the marginal distribution of each outcome allowing for correlation across these marginals. The correlations will be assumed fixed while the mean of the marginals will be allowed to change over time.

5.2 Model and estimation

Assume the latent model for $\mathbf{y}_i^* = (y_{i1}^*, \ldots, y_{iM}^*)'$,

$$\mathbf{y}_i^* = \mu + \varepsilon_i,$$

where ε_i is normally distributed with mean zero and covariance matrix $\mathbf{\Omega}$. It will be useful to write the model as

$$\mathbf{y}_i^* = \mu + \mathbf{L}_\Omega \eta_i,$$

where $\mathbf{L}_\Omega$ is a lower triangular matrix such that $\mathbf{L}_\Omega \mathbf{L}_\Omega' = \mathbf{\Omega}$ and $\eta_i = (\eta_{i1}, \ldots, \eta_{iM})'$ are standard normal. We observe $y_i = \Gamma(y_i^*)$ which is a non-invertible mapping for a subset of the M outcomes. For example, we have binary, ordered and censored outcomes for which integration is necessary.

The vector μ can depend on some variables which have a stable distribution over time $\mathbf{z}_i$ (say race, gender and education). This way, estimation preserves the correlation with these outcomes without having to estimate their correlation with other outcomes. Hence, we can write

$$\mu_i = \mathbf{z}_i \beta$$

and the whole analysis is done conditional on $\mathbf{z}_i$.

For binary and ordered outcomes, we fix $\Omega_{m,m} = 1$ which fixes the scale. Also we fix the location of the ordered models by fixing thresholds as $\tau_0 = -\infty$, $\tau_1 = 0$, $\tau_K = +\infty$, where K denotes the number of categories for a particular outcome. We also fix to zero the correlation between selected outcomes (say earnings) and their selection indicator. Hence, we consider two-part models for these outcomes. Because some parameters are naturally bounded, we also re-parameterize the problem to guarantee an interior solution. In particular, we parameterize

$$\begin{aligned}
\Omega_{m,m} &= \exp(\delta_m), \; m = m_0 - 1, \ldots, M \\
\Omega_{m,n} &= \tanh(\xi_{m,n})\sqrt{\Omega_{m,m}\Omega_{m,n}}, \; m, n = 1, \ldots, N \\
\tau_{m,k} &= \exp(\gamma_{m,k}) + \tau_{k-1}, \; k = 2, \ldots, K_m - 1, m \text{ ordered}
\end{aligned}$$

and estimate the $(\delta_{m,m}, \xi_{m,n}, \gamma_k)$ instead of the original parameters. The parameter values are estimated using the *cmp* package in Stata (Roodman, 2011). Table 16 gives parameter estimates for the indices while Table 17 gives parameter estimates of the covariance matrix in the outcomes.

To apply trends to the future cohorts, the latent model is written as

$$\mathbf{y}_i^* = \mu + \mathbf{L}_\Omega \eta_i.$$

Each marginal has a mean change equal to $\mathrm{E}(\mathbf{y} \mid \mu) = (1+\tau)g(\mu)$, where τ is the percent change in the outcome and $g()$ is a non-linear but monotone mapping. Since it is invertible, we can find the vector μ^* where $\mu^* = g^{-1}(\mathrm{E}(y \mid \mu)/(1+\tau))$. We use these new intercepts to simulate new outcomes.

6 Government revenues and expenditures

This gives a limited overview of how revenues and expenditures of the government are computed. These functions are based on 2004 rules, but we include predicted changes in program rules such changes based on year of birth (e.g. Normal retirement age).

We cover the following revenues and expenditures:

Revenues	**Expenditures**
Federal Income Tax	Social Security Retirement benefits
State and City Income Taxes	Social Security Disability benefits
Social Security Payroll Tax	Supplementary Security Income (SSI)
Medicare Payroll Tax	Medical Care Costs
Property Tax	Medicaid
	Medicare (parts A, B, and D)

6.1 Social Security benefits

Workers with 40 quarters of coverage and of age 62 are eligible to receive their retirement benefit. The benefit is calculated based on the Average Indexed Monthly Earnings (AIME) and the age at which benefits are first received. If an individual claims at his normal retirement age (NRA) (65 for those born prior to 1943, 66 for those between 1943 and 1957, and 67 thereafter), he receives his Primary Insurance Amount (PIA) as a monthly benefit. The PIA is a piece-wise linear function of the AIME. If a worker claims prior to his NRA, his benefit is lower than his PIA. If he retires after the NRA, his benefit is higher. While receiving benefits, earnings are taxed above a certain earning disregard level prior to the NRA. An individual is eligible to half of his spouses PIA, properly adjusted for the claiming age, if that is higher than his/her own retirement benefit. A surviving spouse is eligible to the deceased spouses PIA. Since we assume prices are constant in our simulations, we do not adjust benefits for the COLA (Cost of Living Adjustment) which usually follows inflation. We however adjust the PIA bend points for increases in real wages.

6.2 Disability Insurance benefits

Workers with enough quarters of coverage and under the normal retirement age are eligible for their PIA (no reduction factor) if they are judged disabled (which we take as the predicted outcome of DI receipt) and earnings are under a cap called the Substantial Gainful Activity (SGA) limit. This limit was $9720 in 2004. We ignore the 9 month trial period over a 5 year window in which the SGA is ignored.

6.3 Supplemental Security Income benefits

Self-reported receipt of supplemental security income (SSI) in the HRS provides estimates of the proportion of people receiving SSI under what administrative data would suggest. To correct for this bias, we link the HRS with administrative data from the social security administration identifying those receiving SSI. In the linked administrative data, 3.96% of the population receives supplementary security income, while only 2.79% of the sample reports social security income. We therefore estimate a probit of receiving SSI as a function of self-reporting social security income, as well as demographic, health, and wealth.

The benefit amount is taken from the average monthly benefits found in the 2004 Social Security Annual Statistical Supplement. We assign monthly benefit of $450 for person aged 51 to 64, and $350 for persons aged 65 and older.

6.4 Medical costs estimation

In the FEM, a cost module links a person's current state–demographics, economic status, current health, risk factors, and functional status to 4 types of individual medical spending. The FEM models: total medical spending (medical spending from all payment sources), Medicare spending[5], Medicaid spending (medical spending paid by Medicaid), and out of pocket spending (medical spending by the respondent). These estimates are based on pooled weighted least squares regressions of each type of spending on risk factors, self-reported conditions, and functional status, with spending inflated to constant dollars using the medical component of the consumer price index. We use the 2000-2010 Medical Expenditure Panel Survey for these regressions for persons not Medicare eligible, and the 2000-2010 Medicare Current Beneficiary Survey for spending for those that are eligible for Medicare. Those eligible for Medicare include

[5]We estimate annual medical spending paid by specific parts of Medicare (Parts A, B, and D) and sum to get the total Medicare expenditures.

people eligible due to age (65+) or due to disability status. Comparisons of prevalences and question wording across these different sources are provided in Tables 1 and 2, respectively.

In the baseline scenario, this spending estimate can be interpreted as the resources consumed by the individual given the manner in which medicine is practiced in the United States during the post-part D era (2006-2010). Models are estimated for total, Medicaid, out of pocket spending, and for the Medicare spending. These estimates only use the MCBS dataset.

Since Medicare spending has numerous components (Parts A and B are considered here), models are needed to predict enrollment. In 2004, 98.4% of all Medicare enrollees, and 99%+ of aged enrollees, were in Medicare Part A, and thus we assume that all persons eligible for Medicare take Part A. We use the 2007-2010 MCBS to model take up of Medicare Part B for both new enrollees into Medicare, as well as current enrollees without Part B. Estimates are based on weighted probit regression on various risk factors, demographic, and economic conditions. The HRS starting population for the FEM does not contain information on Medicare enrollment. Therefore another model of Part B enrollment for all persons eligible for Medicare is estimated via a probit, and used in the first year of simulation to assign initial Part B enrollment status. Estimation results are shown in estimates table. The MCBS data over represents the portion enrolled in Part B, having a 97% enrollment rate in 2004 instead of the 93.5% rate given by Medicare Trustee's Report. In addition to this baseline enrollment probit, we apply an elasticity to premiums of -0.10, based on the literature and simulation calibration for actual uptake through 2009 (Atherly et al., 2004; Buchmueller, 2006). The premiums are computed using average Part B costs from the previous time step and the means-testing thresholds established by the ACA.

Since both the MEPS and MCBS are known to under-predict medical spending (see, e.g., Selden and Sing, 2008, and references therein), we applied adjustment factors to the predicted three types of individual medical spending so that the predicted per-capita spending in FEM equal the corresponding spending in National Health Expenditure Accounts (NHEA) for age group 55-64 in year 2004 and ages 65 and over in year 2010, respectively. Table 18 shows how these adjustment factors were determined by using the ratio of expenditures in the NHEA to expenditures predicted in the FEM.

Since 2006, the Medicare Current Beneficiaries Survey (MCBS) contains data on Medicare Part D. The data gives the capitated Part D payment and enrollment. When compared to the summary data presented in the CMS 2007 Trustee Report, the 2006 per capita cost is comparable between the MCBS and the CMS. However, the enrollment is underestimated in the MCBS, 53% compared to 64.6% according to CMS.

A cross-sectional probit model is estimated using years 2007-2010 to link demographics, economic status, current health, and functional status to Part D enrollment - see the estimates table. To account for both the initial under reporting of Part D enrollment in the MCBS, as well as the CMS prediction that Part D enrollment will rise to 75% by 2012, the constant in the probit model is increased by 0.22 in 2006, to 0.56 in 2012 and beyond. The per capita Part D cost in the MCBS matches well with the cost reported from CMS. An OLS regression using demographic, current health, and functional status is estimated for Part D costs based on capitated payment amounts.

The Part D enrollment and cost models are implemented in the Medical Cost module. The Part D enrollment model is executed conditional on the person being eligible for Medicare, and the cost model is executed conditional on the enrollment model leading a true result, after the Monte Carlo decision. Otherwise the person has zero Part D cost. The estimated Part D costs are added with Part A and B costs to obtain total Medicare cost, and any medical cost growth assumptions are then applied.

6.5 Taxes

We consider Federal, State and City taxes paid at the household level. We also calculate Social Security taxes and Medicare taxes. HRS respondents are linked to their spouse in the HRS simulation. We take program rules from the OECD's Taxing Wages Publication for 2004. Households have basic and personal deductions based on marital status and age (>65). Couples are assumed to file jointly. Social Security benefits are partially taxed. The amount taxable increases with other income from 50% to 85%. Low income elderly have access to a special tax credit and the earned income tax credit is applied for individuals younger than 65. We calculate state and city taxes for someone living in Detroit, Michigan. The OECD chose this location because it is generally representative of average state and city taxes paid in the U.S. Since Social Security administrative data cannot be used jointly with Geocoded information in the HRS, we apply these hypothetical taxes to all respondents.

At the state level, there is a basic deduction for each member of the household ($3,100) and taxable income is taxed at a flat rate of 4%. At the city level, there is a small deduction of $750 per household member and the remainder is taxed at a rate of 2.55%. There is however a tax credit that decreases with income (20% on the first 100$ of taxes paid, 10% on the following 50$ and 5% on the remaining portion).

We calculate taxes paid by the employee for Old-Age Social Insurance (SS benefits and DI) and Medicare (Medicaid and Medicare). It does not include the equivalent portion paid by the employer. OASI taxes of 6.2% are levied on earnings up to $97,500 (2004 cap) while the Medicare tax (1.45%) is applied to all earnings.

7 Scenarios and robustness

7.1 Obesity reduction scenario

In addition the to the status quo scenario, the Future Elderly Model can be used to estimate the effects of numerous possible policy changes. One such set of policy simulations involves changing the trends of risk factors for chronic conditions. This is implemented by altering the incoming cohorts. A useful example is an obesity reduction scenario which rolls back the prevalence of obesity among 50 year-olds to its 1978 level by 2030, where it remains until the end of the scenario, in 2050. This is accomplished by reversing the annual rates of change for BMI category, hypertension, and diabetes shown in Table 5. As seen in Table 20, this will change the prevalence of obesity among the age 50+ in 2050. As compared with the status quo estimates (Table 19) the FEM predicts that by 2050, this will result in a change in the amount of Social Security benefits as well as changing combined Medicare and Medicaid expenditures.

8 Implementation

The FEM is implemented in multiple parts. Estimation of the transition and cross sectional models is performed in Stata. The incomong cohort model is estimated in Stata using the CMP package (Roodman, 2011). The simulation is implemented in C++ to increase speed.

To match the two year structure of the Health and Retirement Study (HRS) data used to estimate the transition models, the FEM simulation proceeds in two year increments. The end of each two year step is designed to occur on July 1st to allow for easier matching to population forecasts from Social Security. A simulation of the FEM proceeds by first loading a population representative of the age 51+ US population in 2004, generated from HRS. In two year increments, the FEM applies the transition models for mortality, health, working, wealth, earnings, and benefit claiming with Monte Carlo decisions to calculate the new states of the population. The population is also adjusted by immigration forecasts from the US Census Department, stratified by race and age. If incoming cohorts are being used, the new 51/52 year olds are added to the population. The number of new 51/52 year olds added is consistent with estimates from the Census, stratified by race. Once the new states have been determined and new 51/52 year olds added, the cross sectional models for medical costs, and calculations for government expenditures and revenues are performed. Summary variables are then computed. Computation of medical costs includes the persons that died to account for end of life costs. Other computations, such as Social Security benefits and government tax revenues, are restricted to persons alive at the end of each two year interval. To eliminate uncertainty due to the Monte Carlo decision rules, the simulation is performed multiple times (typically 100), and the mean of each summary variable is calculated across repetitions.

FEM simulation takes as inputs assumptions regarding growth in the national wage index, normal retirement age, real medical cost growth, interest rates, cost of living adjustments, the consumer price index, significant gainful activity, and deferred retirement credit. The default assumptions are taken from the 2010 Social Security Intermediate scenario, adjusted for no price increases after 2010. Therefore simulation results are in real 2009 dollars. Table 21 shows the assumptions for each calendar year and Table 22 shows assumptions for each birth year.

Different simulation scenarios are implemented by changing any of the following components: incoming cohort model, transition models, interventions that adjust the probabilities of specific transition, and changes to assumptions on future economic conditions.

9 Model development

This section gives some historical background about decisions and developments that led up to the current state of the FEM.

9.1 Transition model

Section 4.1 describes the current FEM transition model with a focus on discrete absorbing outcomes. In developing this model, it was previously assumed that the time invariant part of the hazard was composed of the effect of observed characteristics x_i and permanent unobserved characteristics specific to outcome m, $\eta_{i,m}$. Consequently, the index was assumed to be of the form $z_{m,j_i} = x_i\beta_m + h_{i,j_i-1,-m}\gamma_m + \eta_{i,m}$ and the latent component of the hazard was modeled as

$$h^*_{i,j_i,m} = x_i\beta_m + h_{i,j_i-1,-m}\gamma_m + \eta_{i,m} + a_{m,j_i} + \varepsilon_{i,j_i,m}, \tag{6}$$
$$m = 1, \dots, M_0,\ j_i = j_{i0}, \dots, j_{i,T_i},\ i = 1, \dots, N$$

This is the same as (1), except that (6) uses unobserved characteristics $\eta_{i,m}$ instead of the effects of observed initial conditions $h_{i,j_0,-m}\psi_m$. The unobserved effects $\eta_{i,m}$ are persistent over time and were allowed to be correlated across diseases $m = 1, \dots, M$. We assumed that these effects had a normal distribution with covariance matrix $\mathbf{\Omega}_\eta$.

The parameters $\theta_1 = \left(\{\beta_m, \gamma_m, \varsigma_m\}_{m=1}^M, \mathrm{vech}(\mathbf{\Omega}_\eta)\right)$, could be estimated by maximum simulated likelihood. The joint probability, conditional on the individual frailty is the product of normal univariate probabilities. Similar to the joint probability in Section 4.1, these sequences, conditional on unobserved heterogeneity, are also independent across diseases. The joint probability over all disease-specific sequences is simply the product of those probabilities.

For a given respondent with frailty η_i, the probability of the observed health history is (again, omitting the conditioning on covariates for simplicity)

$$l_i^{-0}(\theta; \eta_i, h_{i,j_{i0}}) = \left[\prod_{m=1}^{M-1} \prod_{j=j_{i1}}^{j_{T_i}} P_{ij,m}(\theta; \eta_i)^{(1-h_{ij-1,m})(1-h_{ij,M})}\right] \times \left[\prod_{j=j_{i1}}^{j_{T_i}} P_{ij,M}(\theta; \eta_i)\right]$$

To obtain the likelihood of the parameters given the observables, it is necessary to integrate out unobserved heterogeneity. The complication is that $h_{i,j_{i0},-m}$, the initial outcomes in each hazard, are not likely to be independent of the common unobserved heterogeneity term which needs to be integrated out. A solution is to model the conditional probability distribution $p(\eta_i \mid \mathbf{h}_{i,j_{i0}})$ (Wooldridge, 2000). Implementing this solution amounts to including initial outcomes at baseline (age 50) for each hazard. This is equivalent to writing

$$\eta_i = \Gamma h_{i0} + \alpha_i$$
$$\alpha_i \sim \mathrm{N}(0, \Omega_\alpha)$$

Therefore, this allows for permanent differences in outcomes due to differences in baseline outcomes. The likelihood contribution for one respondent's sequence is therefore given by

$$l_i(\theta, \mathbf{h}_{i,j_{i0}}) = \int l_i(\theta; \alpha_i, \mathbf{h}_{i,j_{i0}}) dF(\alpha_i) \tag{7}$$

This model was estimated using maximum simulated likelihood. The likelihood contribution (7) was replaced with a simulated counterpart based on R draws from the distribution of α. The BFGS algorithm was then used to optimize over this simulated likelihood. Convergence of the joint estimator could not be obtained, so the distribution of α_i was assumed to be degenerate. This yielded the simpler estimation problem describe in Section 4.1, where each equation is estimated separately.

9.2 Quality adjusted life years

9.2.1 Health related quality-of-life measures

In general, HRQoL measures summarize population health by a single preference-based index measure. A HRQoL measure is a suitable measure of QALY. There are several widely-used generic HRQoL indexes, each involving a standard descriptive system: a multidimensional measure of health states and a corresponding scoring system to translate the descriptive system into a single index (Fryback et al., 2007). The scoring system is developed based on a community survey of preference valuation of health states in the descriptive system, using utility valuation methods like time trade-offs or a standard gamble.

9.2.2 Health related quality-of-life in MEPS

Because the health states measures in the HRS and FEM do not match the health states defined in any of the currently available HRQoL indexes, we used MEPS to create a crosswalk file for HRQoL index calculation. MEPS collects information on health care cost and utilization, demographics, functional status, and medical conditions. Since the year 2000, it initiated a self-administered questionnaire for two sets of instruments: SF-12 and EQ-5D.

Seven of the twelve SF-12 questions can be used to generate another HRQoL index: SF-6D. However, the scoring system for SF-6D was derived from a UK sample (Brazier and Roberts, 2004) and a significant proportion of the MEPS sample did not give valid answer for at least one of the seven questions. Therfore, we decided to calculate EQ-5D index score as the HRQoL measure for FEM.

The EQ-5D instrument includes 5 questions about the extent of problems in mobility, self-care, daily activities, pain, and anxiety/depression. The scoring system for EQ-5D was first developed by Dolan (1997) using a UK sample. Later, a scoring system based on a US sample was generated (Shaw et al., 2005). In MEPS 2001, there are 8,301 respondents aged 51 and over. Of those respondents, 7,439 gave valid answers for all of the five EQ-5D questions. We calculated EQ-5D scores for these respondents using the scoring algorithm based on a US sample

(Shaw et al., 2005). The distribution of EQ-5D index scores among these respondents is shown in Figure 2.

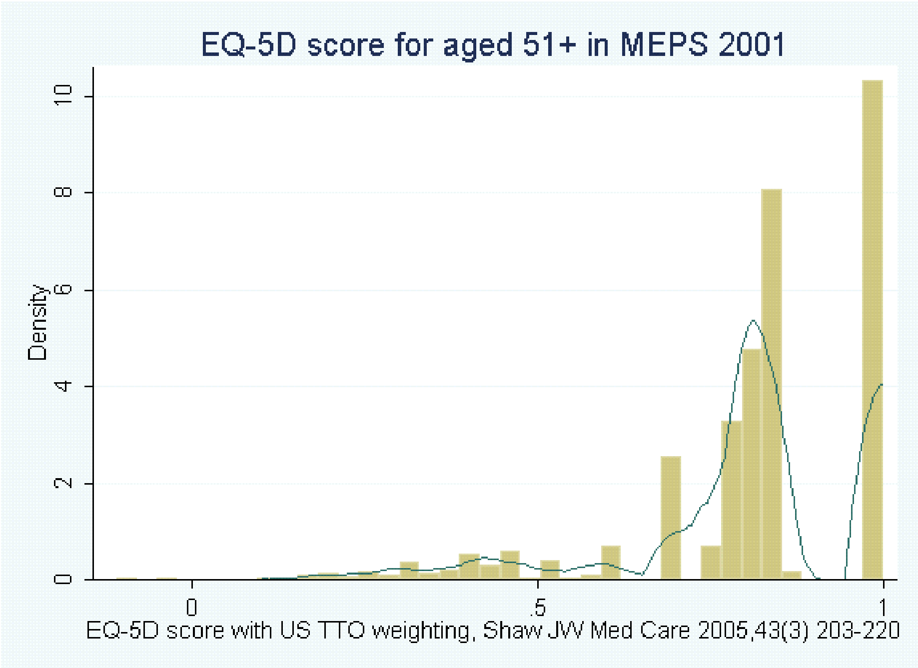

Figure 2: Distribution of EQ-5D index scores for ages 51+ in 2001 MEPS

9.2.3 MEPS-HRS Crosswalk development

The functional status measure in FEM is based on the HRS. It is a categorical variable including the following mutually exclusive categories: healthy, any IADL limitation (no ADL limitations), 1-2 ADL limitations, and 3 or more ADL limitations. Unfortunately the measures of IADL and ADL limitations in MEPS are quite different. HRS asks questions like “Do you have any difficulty in . . .”, while MEPS asks questions like “Does . . .help or supervision in . . ..” As Table 10 shows, the prevalence of IADL limitations is relatively similar between the two surveys, while the prevalence of ADL limitations is much higher in HRS, relative to MEPS. This is reasonable since not all who have difficulty in ADLs receive help or supervision.

In order to compute EQ-5D index scores using functional status in the FEM, we needed a set of functional status measures that is comparable across MEPS and HRS (the host dataset for FEM). We explored several options for deriving such a measure. Ultimately, we constructed two measures. One measure indicates physical function limitation while the other measure indicates IADL limitation.

In MEPS, physical function limitation indicates that at least one of the following is true: 1) receiving help or supervision with bathing, dressing or walking around the house; 2) being limited in work/housework; 3) having difficulty walking, climbing stairs, grasping objects, reaching overhead, lifting, bending or stooping, or standing for long periods of time; or 4) having difficulty in hearing or vision. In HRS, physical function limitation indicates that at least one of the following is true: 1) having any difficulty in bathing/dressing/eating/walking across the room/getting out of bed; 2) limited in work/housework; or 3) limited in any other activities.

In MEPS, IADL limitation indicates receiving help or supervision using the telephone, paying bills, taking medications, preparing light meals, doing laundry, or going shopping. In HRS, IADL limitation indicates having difficulty in any IADL such as using the phone, managing money, or taking medications.

The prevalence of our two constructed measures among ages 51 and older in MEPS (2001) and HRS (1998) is shown in Table 11. The prevalences are quite similar across the two surveys.

Using MEPS 2001 data, we next use ordinary least squares to model the derived EQ-5D score as a function of six chronic conditions – which are available both in HRS and MEPS, our two constructed measures of functional status, and an interaction term of the two measures of functional status. Three different models were considered. Estimation results are presented in Models I-III in Table 12. We also show the estimation results of using only IADL/ADL limitation as covariates, and using only the six chronic conditions as covariates, as Models IV and V in Table 12. Model II was used as the crosswalk described in Section 4.3 to calculate EQ-5D score for non-nursing home residents aged 51 and over in HRS 1998.

9.3 Drug Expenditures

9.3.1 Drug Expenditures - MEPS

AHRQ produces a file of consolidated annual expenditures for each Medical Expenditure Panel Survey respondent in each calendar year. The total drug expenditure variable sums all amounts paid out-ot-pocket and by third party payers for each prescription purchased in that year. For comparison across years, we convert all amounts to 2010 dollars using the Medical CPI.

9.3.2 Drug Expenditures - MCBS

The Medicare Current Beneficiary Survey produces a Prescribed Medicine Events file at the individual-event level, with cost and utilization of prescribed medicines for the MCBS community population. Collapsing this file to the individual provides an estimate of prescription drug cost for each person. For comparison across years, we convert all amounts to 2010 dollars using the Medical CPI.

There are two caveats to working with these data. The first caveat regards how to handle the "ghost" respondents. "Ghosts" are individuals who enroll in Medicare, but were not asked cost and use questions in the year of their enrollment. For some outcomes, such as medical expenditures, the MCBS makes an effort to impute. For others, such as drug utilization and expenditures, the MCBS does not. We imputed annual drug expenditures for the ghosts, but for certain age ranges the drug expenditures were not reasonable. This had the biggest effect on the 65 and 66 year olds, for two reasons. The first is that the 65 and 66 year olds are more likely to be ghosts, as 65 is the typical age of enrollment for Medicare. The second is that the 65 and 66 year olds used for imputation (i.e., the non-"ghosts") are different. To be fully present in MCBS at age 65 would require enrolling in Medicare before age 65, which happen through a different channel, such as qualifying for Medicare due to receiving disability benefits from the federal government.

The second caveat relates to the filling in zeroes for individuals with no utilization data, but who were enrolled. We assumed that individuals who were not ghosts and who did not appear on the Prescribed Medicine Events file had zero prescription expenditures.

9.3.3 Drug Expenditures - Estimation

Due to the complexities of the age 65-66 population in the MCBS, we chose to estimate the drug expenditure models using the MEPS for individuals 51 to 66 and the MCBS for individuals 67 and older. Individuals under age 65 receiving Medicare due to disability are estimated separately. Since there are a number of individuals with zero expenditures, we estimate the models in two stages. The first stage is a probit predicting any drug expenditures and the second is an ordinary least squares model predicting the amount, conditional on any. Coefficient estimates and marginal effects are shown in the accompanying Excel workbook.

10 Tables

				Prevalence %				
Source (years, ages)	Cancer	Heart Diseases	Stroke	Diabetes	Hypertension	Lung Disease	Overweight	Obese
HRS (1991-2008, 55-64)	8%	14%	4%	14%	42%	7%	40%	30%
NHIS (1997-2010, 55-64)	8%	17%	3%	13%	42%	8%	38%	31%
MEPS (2000-2010, 55-64)	7%	16%	4%	14%	46%	7%	38%	32%
HRS (1991-2008, 65+)	16%	30%	11%	17%	55%	10%	38%	20%
NHIS (1997-2010, 65+)	15%	31%	9%	15%	54%	10%	36%	23%
MCBS (2000-2010, 65+)	18%	40%	12%	22%	64%	16%	38%	23%
MEPS (2000-2010, 65+)	12%	33%	11%	19%	63%	9%	38%	24%

Table 1: Health condition prevalences in survey data

	Survey			
Disease	HRS	NHIS	MEPS	MCBS
Cancer	Has a doctor ever told you that you have cancer or a malignant tumor, excluding minor skin cancers?	Have you ever been told be a doctor or other health professional that you had cancer or a malignanacy of any kind? (WHEN RECODED, SKIN CANCERS WERE EXCLUDED)	List all the conditions that have bothered (the person) from (START time) to (END time) CCS codes for the conditions list are 11-21, 24-45	Has a doctor ever told you that you had any (other) kind of cancer malignancy, or tumor other than skin cancer?
Heart Diseases	Has a doctor ever told you that you had a heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems?	Four separate questions were asked about whether ever told by a docotor or oither health professional that had: CHD, Angina, MI, other heart problems.	Have you ever been told by a doctor or health professional that you have CHD; Angina; MI; other heart problems	Six separate questions were asked about whether ever told by a doctor that had: Angina or MI; CHD; other heart problems (included four questions)
Stroke	Has a doctor ever told you that you had a stroke?	Have you EVER been told by a doctor or other health professional that you had a stroke?	If Female, add: [Other than during pregnancy,] Have you ever been told by a doctor or health professional that you have a stroke or TIA (transient ischemic attack)	[Since (PREV< SUPP. RD. INT. DATE),] has a doctor (ever) told (you/SP) that (you/he/she) had a stroke, a brain hemorrhage, or a cerebrovascular accident?
Diabetes	Has a doctor ever told you that you have diabetes or high blood sugar?	If Female, add: [Other than during pregnancy,] Have you ever been told by a doctor or health professional that you have diabetes or sugar diabetes?	If Female, add: [Other than during pregnancy,] Have you hever been told by a doctor or health professional that you have diabetes or sugar diabetes?	Has a doctor (ever) told (you/SP) that (you/he/she) had diabetes, high blood sugar, or sugar in (your/his/her) urine? [DO NOT INCLUDE BOERDERLINE PREGNANCY, OR PREDIABETEIC DIABETES.]
Hypertension	Has a doctor ver told you that you have high blood pressure or hypertension?	Have you EVER been told by a doctor or other health professional that you had Hypertension, also called high blood pressure?	Have you EVER been told by a doctor or other health professional that you had Hypertension, also called high blood pressure?	Has a doctor (ever) told (you/SP) that (you/he/she) (still) (had) (have/has) hypertension, sometimes called high blood pressure?
Lung Disease	Has a doctor ever told you that you have chronic lung disease such a schronic bronchitis or emphysema? [IWER: DO NOT INCLUDE ASTHMA]	Question 1: During the PAST 12 MONTHS, have you ever been told by a doctor or other health professional that you had chronic bronchitis? Question 2: Have you EVER been told by a docotor or other health professional that you had emphysema?	List all the conditions that have bothered (the person) from (START time) to (END time) CCS codes for the conditions list are 127, 129-312	Has a doctor (ever) told (you/SP) that (you/he/she) had emphysema, asthma, or COPD? [COPD=CHRONIC OBSTRUCTIVE PULMONARY DISEASE.]
Overweight	Self-reported body weight and height			
Obese				

Table 2: Survey questions used to determine health conditions

Conditions	Data source	Projection method	Other sources
Diabetes Heart disease Hypertension	National Health Interview Survey 1997-2006	Use synthetic cohort approach to estimate age-specific incidence rate for each condition	There are other forecasts (Honeycutt et al., 2003; Mainous III et al., 2007) for the trends of diabetes in the U.S population; we compare their forecasts to ours and they are reasonably close
Overweight and obese	Prevalence of over-weight and obese for aged 46-56 from year 2001 to 2030, generated by Ruhm upon request	Assume annual rate of change during year 2031-2050 linearly decreases from the 2030 rate to zero in 2050	Ruhm (2007)
Ever-smoked and smoking now	Forecast of prevalence of ever-smoked and smoking now for aged 45-54 from year 2005 to 2025, by Levy (2006)	For ever-smoked, assume that the prevalence at age 45-54 in year 2035 (2045) is the same as prevalence at age 35-44 (25-34) in year 2025. Assume that the annual change in prevalence at age 45-54 in year 2046-2050 the same as average in 2040-2045. For smoking-now, after year 2025, use the moving average of the past five years	
Any DB from current job		Assume annual relative declining rate for DB entitlement decrease by 2% a year	Historical trends of DB participation rates among all persons by different birth cohorts and by age, by Poterba et al. (2007)
Any DC from current job		Assume annual relative increasing rate for DC entitlement increase by 2% a year until 2026 then stays the same after 2026	Forecast of DC participation rates among all persons by different birth cohorts and by age, by Poterba et al. (2008)
Population size 50-52 Male Hispanic Non-Hispanic black	Census Bureau 2000-2010 Intercensal Population Estimates, 2012 National Population Estimates, and 2012 National Population Projections	Projected 2060 - 2080 using linear trend based on 2040-2060	

Table 3: Data sources and methods for projecting future cohort trends

Ratio of future prevalence to 2004 prevalence for 51-52 year olds

	Binary outcomes			Ordered outcomes (highest category)		Censored discrete outcomes	
Year	Hypertension	Heart Disease	Diabetes	BMI Status (BMI≥40)	Smoking Status (smoking now)	Any DB Plan	Any DC Plan
2004	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2010	1.04	0.95	1.12	1.24	0.94	0.89	1.14
2020	1.07	0.91	1.22	1.72	0.73	0.72	1.41
2030	1.09	0.88	1.27	2.38	0.60	0.59	1.56
2040	1.11	0.85	1.31	3.03	0.50	0.48	1.56
2050	1.13	0.83	1.36	3.28	0.41	0.39	1.56

Table 4: Projected baseline trends for future cohorts

	Prevalence		
Condition	1978	2004	Annual rate of change to get 1978 prevalence by 2030
$30 \leq$ BMI < 35 (kg/m^2)	0.112	0.230	-0.027
$35 \leq$ BMI < 40 (kg/m^2)	0.028	0.060	-0.029
BMI >= 40 (kg/m^2)	0.014	0.040	-0.040
Hypertension	0.326	0.338	-0.001
Diabetes	0.047	0.103	-0.030
Currently smoking	0.398	0.281	0.013

Table 5: Prevalence of obesity, hypertension, diabetes and current smokers among ages 46-56 in 1978 and 2004. Prevalence in 1978 is based on NHANES II 1976-1980; Prevalence in 2004 is based on NHANES 2003-2004. BMI is calculated using self-reported weight and height.

			Type	At risk	Mean/fraction
Disease	heart disease		biennial incidence	undiagnosed	0.03
	hypertension		biennial incidence	undiagnosed	0.04
	stroke		biennial incidence	undiagnosed	0.01
	lung disease		biennial incidence	undiagnosed	0.01
	cancer		biennial incidence	undiagnosed	0.02
	diabetes		biennial incidence	undiagnosed	0.02
Risk Factors	Smoking Status	never smoked	ordered	all	0.42
		ex smoker	ordered	all	0.43
		current smoker	ordered	all	0.15
	Log BMI		continuous	all	3.29
	ADL Status	no ADLs	ordered	all	0.78
		1 ADL	ordered	all	0.08
		2 ADLS	ordered	all	0.03
		3+ ADLS	ordered	all	0.05
	IADL Status	no IADLs	ordered	all	0.85
		1 IADL	ordered	all	0.05
		2+ IADLs	ordered	all	0.04
LFP & Benefits	working		prevalence	age < 80	0.49
	DB pension receipt		biennial incidence	eligible & not receiving	0.08
	SS benefit receipt		biennial incidence	eligible & not receiving	0.07
	DI benefit receipt		prevalence	eligible & age < 65	0.04
	Any health insurance		prevalence	age < 65	0.88
	SSI receipt		prevalence	all	0.03
	Nursing Home residency		prevalence	all	0.02
	Death		biennial incidence	all	0.06
Financial Resources ($USD 2004)	financial wealth		median	all non-zero wealth	166,014.16
	earnings		median	all working	6,581.92
	wealth positive		prevalence	all	0.97

Table 6: Outcomes in the transition model. Estimation sample is HRS 1991-2008 waves.

Value at time $T-1$	Outcome at time T																			
	Heart disease	hypertension	stroke	Lung disease	diabetes	cancer	disability	mortality	Smoking status	BMI	Any HI	DI Claim	SS Claim	DB Claim	SSI Claim	Nursing Home	Work	Earnings	Nonzero Wealth	Wealth
Heart disease			✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Blood pressure	✓		✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Stroke							✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lung disease							✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Diabetes	✓	✓	✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cancer			✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Disability							✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Claimed DI											✓	✓	✓	✓	✓		✓	✓	✓	✓
Claimed SS											✓			✓	✓		✓	✓	✓	✓
Claimed DB													✓		✓		✓	✓	✓	✓
Claimed SSI															✓					
Work											✓	✓	✓		✓		✓	✓	✓	✓
Earnings											✓	✓	✓	✓	✓		✓	✓	✓	✓
Nonzero wealth											✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Wealth											✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Nursing home stay															✓	✓			✓	✓

Table 7: Restrictions on transition model. ✓indicates that an outcome at time $T-1$ is allowed in the transition model for an outcome at time T.

	Unweighted Statistics			
Control variable	Mean	Standard deviation	Minimum	Maximum
Non-Hispanic black	0.128	0.335	0	1
Hispanic	0.0791	0.270	0	1
Less than high school	0.249	0.433	0	1
Some college and above	0.392	0.488	0	1
Male	0.432	0.495	0	1
Ever smoked	0.600	0.490	0	1
fraime	1885	1501	0.359	8429
frq	104.8	54.87	1	216
Init.of Any DB from current job RND VG	0.168	0.374	0	1
fnra3	0.0470	0.212	0	1
fnra4	0.0284	0.166	0	1
fnra5	0.0630	0.243	0	1
Any DC from current job RND VG	0.138	0.345	0	1
(IHT of DC wlth in 1000s)/100 if any DC zero otherwise	0.00477	0.0134	0	0.0782

Table 8: Desciptive statistics for exogeneous control variables in 2004 HRS ages 51+ sample used as simulation stock population

	1998			2004			2008		
Outcome	FEM mean	HRS mean	*p*	FEM mean	HRS mean	*p*	FEM mean	HRS mean	*p*
One ADL limitation	0.070	0.073	0.130	0.085	0.084	0.583	0.092	0.091	0.817
Two ADL limitations	0.030	0.034	0.017	0.034	0.036	0.233	0.040	0.034	0.003
Three or more ADL limitations	0.049	0.042	0.000	0.048	0.039	0.000	0.059	0.047	0.000
Exact Age at July 1st	65.769	65.865	0.262	69.741	69.763	0.796	72.442	72.310	0.123
Any health insurance coverage (gov/emp/other)	0.944	0.944	0.866	0.971	0.959	0.000	0.983	0.973	0.000
Non-hispanic black	0.087	0.090	0.215	0.084	0.086	0.419	0.082	0.083	0.804
R Body mass index	26.929	26.855	0.085	27.326	27.257	0.181	27.576	27.795	0.000
R ever had cancer	0.099	0.100	0.698	0.150	0.148	0.532	0.182	0.180	0.610
Claiming DB waves 4-7	0.000	0.036	0.000	0.057	0.083	0.000	0.094	0.000	0.000
R ever had diabetes	0.118	0.122	0.100	0.181	0.176	0.159	0.218	0.224	0.159
Claiming SSDI	0.036	0.037	0.687	0.023	0.032	0.000	0.014	0.024	0.000
HH wlth in 1000s if positive-max 2000 zero otherwise	309.175	274.201	0.000	405.977	375.756	0.000	423.601	439.422	0.003
R ever had heart disease	0.166	0.197	0.000	0.239	0.255	0.000	0.294	0.295	0.673
R ever had hypertension	0.418	0.419	0.823	0.545	0.545	0.914	0.619	0.632	0.007
HH capital income	13202.310	14742.810	0.034	15369.840	13420.510	0.003	15715.010	16080.520	0.620
Household Capital Income is not zero	0.698	0.737	0.000	0.725	0.709	0.000	0.745	0.685	0.000
Hispanic	0.061	0.062	0.980	0.065	0.059	0.010	0.066	0.063	0.162
One IADL limitation	0.045	0.048	0.063	0.051	0.054	0.288	0.058	0.057	0.625
Two or more IADL limitations	0.025	0.028	0.090	0.032	0.029	0.162	0.036	0.035	0.610
Individual earnings in 1000s-max 200	15.651	13.941	0.000	11.177	12.446	0.000	8.805	10.717	0.000
R ever had lung disease	0.064	0.069	0.010	0.099	0.098	0.736	0.117	0.120	0.337
Male	0.450	0.447	0.390	0.443	0.448	0.229	0.438	0.443	0.253
R smokes now	0.182	0.174	0.008	0.138	0.137	0.707	0.119	0.120	0.663
R smoke ever	0.593	0.597	0.378	0.581	0.590	0.062	0.570	0.583	0.010
Claiming SSI	0.035	0.036	0.468	0.019	0.021	0.363	0.015	0.018	0.005
R ever had stroke	0.059	0.065	0.004	0.086	0.085	0.509	0.107	0.102	0.090
Non-pension wlth(hatota) not zero	0.968	0.970	0.328	0.973	0.976	0.019	0.974	0.976	0.247
R working for pay	0.437	0.425	0.006	0.330	0.343	0.004	0.254	0.285	0.000

Table 9: Simulated and actual outcomes in 1998, 2004, and 2008

		MEPS 2001 (ages 51+) ADL limitation		
		No	Yes	All
IADL limitation	No	91.5	0.4	92.0
	Yes	4.4	3.7	8.0
	All	95.9	4.1	100.0

		HRS 1998 (ages 51+) ADL limitation		
		No	Yes	All
IADL limitation	No	82.0	10.5	92.5
	Yes	3.1	4.5	7.5
	All	85.1	14.9	100.0

Table 10: Prevalence of IADL and ADL limitations among ages 51+ in MEPS 2001 and HRS 1998. The IADL limitations in MEPS are defined as receiving help or supervision using the telephone, paying bills, taking medications, preparing light meals, doing laundry, or going shopping; the ADL limitations in HRS are defined as receiving help or supervision with personal care such as bathing, dressing, or getting around the house. The IADL limitations in HRS are defined as having any difficulty in at least one of the following activities: using the phone, taking medications, and managing money. The ADL limitations in HRS are defined as having any difficulty in at least one of the following activities: bathing, dressing, eating, walking across the room, and getting out of bed.

		MEPS 2001 (ages 51+) Physical function limitation		
		No	Yes	All
IADL limitation	No	61.6	30.4	92.0
	Yes	0.3	7.8	8.0
	All	61.9	38.2	100.0

		HRS 1998 (ages 51+) Physical function limitation		
		No	Yes	All
IADL limitation	No	60.0	32.5	92.5
	Yes	1.0	6.5	7.5
	All	61.0	39.0	100.0

Table 11: Prevalence of IADL limitation and physical function limitation among ages 51+ in MEPS 2001 and HRS 1998. The definition of IADL limitation is the same as in Table 10. Physical function limitation in MEPS indicates that at least one of the following is true: 1) receiving help or supervision with bathing, dressing or walking around the house; 2) being limited in work/housework; 3) having difficulty walking, climbing stairs, grasping objects, reaching overhead, lifting, bending or stooping, or standing for long periods of time; or 4) having difficulty in hearing or vision. Physical function limitation in HRS indicates at least one of the following is true: 1) having any difficulty in bathing/dressing/eating/walking across the room/getting out of bed; 2) limited in work/housework; or 3) limited in any other activities.

	Model I	Model II	Model III	Model IV	Model V
Constant	0.877***	0.898***	0.874***	0.839***	0.869***
	(0.002)	(0.003)	(0.005)	(0.002)	(0.003)
Physical function limitation	-0.115***	-0.098***	-0.094***		
	(0.004)	(0.005)	(0.004)		
IADL limitation	-0.041	-0.019	-0.008		
	(0.037)	(0.042)	(0.036)		
IADL limitation * Physical function limitation	-0.150***	-0.156***	-0.162***		
	(0.037)	(0.044)	(0.037)		
IADL limitation, no ADL limitation				-0.182***	
				(0.009)	
Any ADL limitation				-0.344***	
				(0.010)	
Ever diagnosed with cancer		-0.011	-0.015**		-0.030***
		(0.009)	(0.007)		(0.010)
Ever diagnosed with diabetes		-0.034***	-0.032***		-0.054***
		(0.007)	(0.005)		(0.007)
Ever diagnosed with high blood pressure		-0.030***	-0.028***		-0.043***
		(0.004)	(0.004)		(0.005)
Ever diagnosed with heart disease		-0.024***	-0.029***		-0.055***
		(0.006)	(0.005)		(0.006)
Ever diagnosed with lung disease		-0.036***	-0.032***		-0.055***
		(0.009)	(0.007)		(0.010)
Ever diagnosed with stroke		-0.045***	-0.046***		-0.115***
		(0.012)	(0.008)		(0.013)
Age 65-74			0.010**		
			(0.004)		
Age 75 and over			0.015***		
			(0.005)		
Male			0.028***		
			(0.004)		
Non-Hispanic black			0.008		
			(0.007)		
Hispanic			-0.001		
			(0.007)		
Less than HS			-0.022***		
			(0.005)		
Some college			0.016***		
			(0.005)		
College grad			0.037***		
			(0.005)		
Census region: Northeast			0.003		
			(0.005)		
Census region: Midwest			0.004		
			(0.005)		
Census region: West			-0.012**		
			(0.005)		
Marital status:widowed			0.003		
			(0.005)		
Marital status: single			-0.013***		
			(0.005)		
N	7,358	7,317	7,317	7,361	7,322
Adjusted R^2	.24	.27	.29	.18	.11

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: OLS regressions of EQ-5D utility index among ages 51+ in MEPS 2001. p-values in parentheses. Data source: MEPS 2001 (ages 51+). EQ-5D scoring algorithm is based on Shaw et al. (2005).

Ever diagnosed with cancer	-0.020*
	(0.001)
Ever diagnosed with diabetes	-0.042*
	(0.001)
Ever diagnosed with heart disease	-0.044*
	(0.001)
Ever diagnosed with high blood pressure	-0.034*
	(0.001)
Ever diagnosed with lung disease	-0.054*
	(0.001)
Ever diagnosed with stroke	-0.067*
	(0.002)
IADL limitation only	-0.160*
	(0.002)
One or two ADL limitations	-0.099*
	(0.001)
Three or more ADL limitations	-0.149*
	(0.002)
Constant	0.881*
	(0.001)
N	19,676
Adjusted R^2	0.67

* $p < 0.01$

Table 13: OLS regression of the predicted EQ-5D index score against chronic conditions and FEM-type functional status specification. p-values in parentheses. Data source: Health and Retirement Study, 1998. Sample included the age 51 and over community respondents. EQ-5D score was predicted using Model II in Table 12.

				Prevalence of chronic conditions					
Functional status	Estimate	Predicted EQ-5D score	Age	Cancer	Diabetes	Heart disease	Hypertension	Lung disease	Stroke
Healthy	Mean	0.841	63.9	0.114	0.142	0.189	0.481	0.072	0.045
	Sd	0.042	10.0	0.318	0.349	0.391	0.500	0.258	0.207
	Std. err	0.000	0.0	0.001	0.001	0.001	0.001	0.001	0.001
IADL limitation only - not in nursing home	Mean	0.655	70.0	0.151	0.223	0.334	0.581	0.152	0.162
	Sd	0.054	12.9	0.358	0.416	0.472	0.493	0.359	0.368
	Std. err	0.001	0.2	0.005	0.005	0.006	0.006	0.005	0.005
1 or 2 ADL limitations - not in nursing home	Mean	0.705	69.1	0.180	0.291	0.393	0.665	0.194	0.162
	Sd	0.057	12.0	0.384	0.454	0.488	0.472	0.395	0.368
	Std. err	0.000	0.1	0.003	0.003	0.004	0.003	0.003	0.003
3 or more ADL limitations - not in nursing home	Mean	0.636	70.9	0.181	0.361	0.467	0.691	0.216	0.314
	Sd	0.063	13.2	0.385	0.480	0.499	0.462	0.412	0.464
	Std. err	0.001	0.2	0.005	0.006	0.006	0.006	0.005	0.006
Nursing home residency	Mean	0.568	82.0	0.144	0.256	0.428	0.651	0.142	0.372
	Sd	0.077	10.0	0.351	0.437	0.495	0.477	0.349	0.484
	Std. err	0.001	0.2	0.006	0.008	0.009	0.008	0.006	0.009
All	Mean	0.808	65.2	0.125	0.170	0.229	0.514	0.094	0.076
	Sd	0.083	10.9	0.331	0.375	0.420	0.500	0.291	0.266
	Std. err	0.000	0.0	0.001	0.001	0.001	0.001	0.001	0.001

Table 14: Average predicted EQ-5D score, age, and prevalence of chronic conditions by functional status for the stock FEM simulation sample (ages 51 and over in 2004). EQ-5D scores were predicted according to parameter estimates in Table 13. The predicted score for nursing home residents is reduced by 10% to account for the fact that the estimation sample in Table 13 only includes non-nursing home residents.

			Selection	1992	2004
Binary	working for pay		all	0.75	0.81
	non-zero wealth		all	0.97	0.98
	hypertension		all	0.30	0.34
	heart disease		all	0.09	0.10
	diabetes		all	0.07	0.08
	any health insurance		all	0.86	0.89
	SRH fair or poor		all	0.17	
Ordered	BMI status	normal	all	0.36	0.27
		overweight	all	0.40	0.41
		$30 \leq \text{BMI} < 35$	all	0.17	0.21
		$35 \leq \text{BMI} < 40$	all	0.05	0.08
		$\text{BMI} \geq 40$	all	0.02	0.04
	Smoking status	never smoked	all	0.36	0.43
		former smoker	all	0.35	0.33
		current smoker	all	0.29	0.24
	Functional status	no ADL	all	0.91	0.91
		no IADL	all	0.90	0.94
Continuous	AIME (nominal $USD)		all	1,922.87	2,008.36
	quarters of coverage		all	93.57	92.33
Censored continuous	earnings		if working	39,988.67	42,968.93
	wealth		if non-zero	253,009.94	285,479.97
	DC wealth		if dc plan	17.12	21.96
Censored discrete	any DB plan		if working	0.29	0.31
	any DC plan		if working	0.26	0.28
Censored ordered	Early age eligible DB	<52		0.19	
		52-57		0.59	
		58>		0.21	
	Normal age eligible DB	<57		0.17	
		57-61		0.26	
		62-63		0.16	
		64>		0.40	
Covariates	hispanic		all	0.07	0.09
	black		all	0.09	0.11
	male		all	0.47	0.49
	less high school		all	0.21	0.09
	college		all	0.40	0.63
	single		all	0.18	0.26
	widowed		all	0.04	0.02
	cancer		all	0.04	0.05
	lunge disease		all	0.05	0.04

Table 15: Initial conditions used for estimation (1992) and simulation (2004)

Covariate	Hypertension	Heart disease	Diabetes	Any health insurance	Self-reported health	Weight status	Smoking status	Functional status (ADL)	Functional status (IADL)	Working	Nonzero wealth	AIME	Quarters worked	IHT(HH wealth)	IHT(earned income)	Log(DC wealth)	Any DC plan	Any DB plan	Early retirement age	Normal retirement age
Non-Hispanic black	0.53	0.03	0.41	-0.16	0.52	0.35	-0.10	0.34	0.31	-0.14	-0.95	-351.70	-5.46	-17.10	-0.41	-0.03	-0.02	0.05	-0.17	-0.13
Hispanic	-0.00	-0.18	0.30	-0.70	0.48	0.18	-0.33	0.25	0.29	-0.14	-0.87	-586.11	-18.59	-15.65	-2.40	-0.04	-0.22	-0.18	-0.02	0.01
Less than high school	0.11	0.12	0.25	-0.53	0.46	0.09	0.30	0.23	0.37	-0.32	-0.33	-412.01	-12.54	-12.44	-2.72	-0.05	-0.26	-0.28	0.26	0.00
Some college and above	-0.06	-0.08	-0.02	0.19	-0.38	-0.16	-0.11	-0.24	-0.34	0.28	0.63	234.75	-3.87	11.24	4.54	0.09	0.27	0.09	-0.21	-0.32
Male	0.10	0.26	0.04	0.07	0.01	0.11	0.42	-0.08	-0.16	0.49	0.20	1641.07	46.07	-2.21	6.11	0.11	0.12	0.05	-0.22	0.03
Single	0.18	-0.01	0.06	-0.22	0.20	-0.04	0.27	0.05	0.01	0.07	-0.98	80.79	4.87	-22.27	0.53	-0.02	0.04	-0.01	-0.07	0.08
Widowed	0.14	0.06	0.03	-0.38	0.36	0.17	0.26	0.06	-0.02	0.07	-1.01	12.73	1.82	-16.53	0.40	-0.08	0.14	-0.05	-0.03	0.11
Lung disease	0.17	0.70	0.43	-0.10	1.04	0.05	0.65	0.85	0.16	-0.50	0.06	-206.13	-3.37	-14.65	-1.38	-0.02	-0.13	0.08	0.07	0.10
Cancer	0.00	0.27	0.07	0.32	0.57	-0.14	0.22	0.45	0.06	-0.22	0.11	6.27	0.98	0.26	1.17	-0.04	0.04	-0.17	0.14	-0.03
constant	-0.68	-1.49	-1.70	1.31	-1.18	0.31	0.10	-1.47	-1.29	0.48	2.64	1185.79	76.74	60.76	13.24	0.60	-0.58	-0.29	1.03	1.10

Table 16: Parameter estimates for latent model: conditional means and thresholds. Sample is respondents age 50-55 in 1992 HRS wave

	Hypertension	Heart disease	Diabetes	Any health insurance	Self-reported health	Weight status	Smoking status	Functional status (ADL)	Functional status (IADL)	Working	Nonzero wealth	AIME	Quarters worked	IHT(HH wealth)	IHT(earned income)	Log(DC wealth)	Any DC plan	Any DB plan	Early retirement age	Normal retirement age
Hypertension	1.000																			
Heart Disease	0.313	1.000																		
Diabetes	0.316	0.228	1.000																	
Any health insurance	-0.017	0.008	0.000	1.000																
Self-repoted health	0.350	0.491	0.447	-0.078	1.000															
Weight status	0.297	0.126	0.250	0.010	0.182	1.000														
Smoking status	-0.005	0.018	-0.005	-0.070	0.059	-0.092	1.000													
Functional status (ADL)	0.228	0.303	0.252	-0.068	0.498	0.132	0.025	1.000												
Functional status (IADL)	0.095	0.090	0.103	-0.053	0.144	0.015	-0.014	0.211	1.000											
Working	-0.168	-0.303	-0.238	0.175	-0.430	-0.019	-0.041	-0.385	-0.189	1.000										
Nonzero wealth	-0.141	-0.158	-0.080	0.218	-0.218	0.006	-0.043	-0.113	-0.171	0.386	1.000									
AIME	-0.668	-73.375	-70.239	320.245	-174.768	32.213	-35.980	-188.171	-134.122	345.162	406.365	1.1e+06								
Quarters worked	-1.157	-3.585	-2.382	7.521	-4.987	0.515	0.949	-4.741	-5.419	15.000	13.507	2.9e+04	1311.883							
IHT(HH wealth)	-1.698	-1.986	-4.563	5.329	-5.629	-1.933	-3.895	-5.951	-2.405	2.128	0.000	5983.905	102.353	903.910						
IHT(earned income)	0.177	0.058	-0.284	2.940	-1.043	-0.066	-0.227	-1.197	-0.911	0.000	2.388	3188.351	46.722	45.945	64.580					
Log(DC wealth)	0.011	-0.001	-0.005	0.052	-0.018	-0.019	-0.006	0.003	-0.018	0.000	0.004	71.853	1.470	1.870	0.725	0.053				
Any DC plan	0.005	0.067	0.063	0.354	-0.065	-0.031	-0.027	-0.062	-0.069	0.000	0.177	300.533	7.307	1.758	3.063	0.000	1.000			
Any DB plan	0.053	0.017	-0.025	0.426	-0.016	0.009	-0.035	-0.024	0.003	0.000	0.101	136.550	1.267	0.777	2.465	0.037	0.136	1.000		
Early retirement age	0.082	0.041	0.071	-0.058	0.110	0.017	0.013	0.101	0.037	0.000	0.010	-30.466	1.521	-2.556	-1.759	-0.025	-0.051	0.000	1.000	
Normal retirement age	0.014	0.040	0.109	0.103	0.158	0.020	0.022	0.040	0.023	0.000	0.009	23.093	4.200	-3.425	-1.315	-0.011	0.015	0.000	0.292	1.000

Table 17: Parameter estimates for latent model: parameterized covariance matrix. Sample is respondents age 50-55 in 1992 HRS wave

	Ages 55-64			Ages 65 and over		
Payment sources	NHEA 2004 ($) (A)	FEM 2004, unadjusted ($) (B)	Adjustment factor (A)/(B)	NHEA 2010 ($) (C)	FEM 2010, unadjusted ($) (D)	Adjustment factor (C)/(D)
Total	7787.00	7074.55	1.10	18424.00	16820.03	1.10
Medicare	706.00	633.40	1.11	10016.00	9236.88	1.08
Medicaid	1026.00	626.11	1.64	2047.00	1537.13	1.33

Table 18: Per capita medical spending by payment source, age group, and year

Year	2010	2030	2050
Population 51+ (Million)	98.24	128.87	150.27
Population 65+ (Million)	43.59	73.66	84.36
Prevalence of selected conditions for ages 51+			
Obesity (BMI >= 30) (%)	0.34	0.48	0.54
Overweight (25 <= BMI < 30) (%)	0.36	0.32	0.29
Ever-smoked	0.56	0.44	0.31
Smoking now	0.15	0.09	0.06
Diabetes	0.19	0.32	0.39
Heart disease	0.22	0.31	0.33
Hypertension	0.55	0.67	0.69
Labor participation for ages 51+			
Working (%)	0.47	0.41	0.41
Average earnings if working ($2010)	47964.75	56642.52	71129.59
Government revenues from ages 51+ (Billion $2010)			
Federal personal income taxes	385.29	622.41	1044.71
Social security payroll taxes	120.72	186.64	290.07
Medicare payroll taxes	32.02	45.16	68.42
Total Revenue	538.04	854.21	1403.21
Government expenditures from ages 51+ (Billion $2010)			
Old Age and Survivors Insurance benefits (OASI)	668.82	1267.96	1716.61
Disability Insurance benefits (DI)	32.05	40.34	59.94
Supplementary Security Income (SSI)	19.09	25.30	37.04
Medicare costs	547.64	1340.99	2661.19
Medicaid costs	172.57	329.67	772.63
Medicare + Medicaid	1440.17	3004.26	5247.41
Total medical costs for ages 51+ (Billion $2010)	1363.76	2968.66	5912.78

Table 19: Simulation results for status quo scenario

	"Obese 1980" Estimates		Relative Change from Status Quo		Absolute Change from Status Quo	
Year	2030	2050	2030	2050	2030	2050
Population 51+ (Million)	129.64	154.58	0.01	0.03	0.77	4.32
Population 65+ (Million)	74.24	88.39	0.01	0.05	0.58	4.04
Prevalence of selected conditions for ages 51+						
Obesity (BMI >= 30) (%)	0.36	0.32	-0.25	-0.41	-0.12	-0.22
Overweight (25 <= BMI < 30) (%)	0.36	0.39	0.15	0.34	0.05	0.10
Ever-smoked	0.44	0.32	-0.00	0.02	-0.00	0.01
Smoking now	0.09	0.06	0.01	0.00	0.00	0.00
Diabetes	0.26	0.25	-0.20	-0.35	-0.06	-0.14
Heart disease	0.29	0.28	-0.08	-0.14	-0.03	-0.05
Hypertension	0.61	0.60	-0.08	-0.13	-0.06	-0.09
Labor participation for ages 51+						
Working (%)	0.43	0.43	0.04	0.05	0.02	0.02
Average earnings if working ($2010)	57,650.77	72,670.16	0.02	0.02	1,008.24	1,540.56
Government revenues from ages 51+ (Billion $2010)						
Federal personal income taxes	671.72	1,183.70	0.08	0.13	49.30	138.99
Social security payroll taxes	198.81	323.09	0.07	0.11	12.17	33.01
Medicare payroll taxes	48.18	76.25	0.07	0.11	3.02	7.83
Total Revenue						
Government expenditures from ages 51+ (Billion $2010)						
Old Age and Survivors Insurance benefits (OASI)	1,272.72	1,786.63	0.00	0.04	4.76	70.02
Disability Insurance benefits (DI)	31.83	40.12	-0.21	-0.33	-8.51	-19.82
Supplementary Security Income (SSI)	24.37	35.15	-0.04	-0.05	-0.94	-1.89
Medicare costs	1,301.63	2,512.88	-0.03	-0.06	-39.36	-148.31
Medicaid costs	319.26	735.67	-0.03	-0.05	-10.41	-36.95
Medicare + Medicaid						
Total medical costs for ages 51+ (Billion $2010)	2,862.30	5,578.12	-0.04	-0.06	-106.36	-334.66

Table 20: Simulation results for obesity reduction scenario compared to status quo

Calendar year	National Wage Index	Real interest rate on wealth	COLA	Consumer Price Index	Substantial Gainful Activity	Y-o-Y excess real growth in medical costs
2004	35648.55	154.7553	3.606042	188.9	9720	.015
2005	36952.94	157.0766	3.703405	195.3	9960	.0148
2006	38651.41	158.3332	3.855245	201.6	10320	.0147
2007	40405.48	160.0749	3.982468	207.342	10800	.0145
2008	41334.97	163.1163	4.074064	215.303	11280	.0143
2009	42188.9	163.7688	4.31036	214.537	11760	.0141
2010	42907.15	171.4659	4.31036	214.537	12000	.0139
2011	43620.13	173.6949	4.31036	214.537	12000	.0138
2012	44197.64	176.4741	4.31036	214.537	12120	.0136
2013	44678.93	180.533	4.31036	214.537	12480	.0134
2014	45126.4	185.2268	4.31036	214.537	12840	.0133
2015	45737.88	190.7836	4.31036	214.537	13080	.0131
2016	46166.54	196.8887	4.31036	214.537	12699.34	.0129
2017	46633.77	202.5985	4.31036	214.537	12827.86	.0128
2018	47117.93	208.2712	4.31036	214.537	12961.05	.0126
2019	47609.11	214.1028	4.31036	214.537	13096.16	.0124
2020	48107.48	220.0977	4.31036	214.537	13233.25	.0122
2021	48615.77	226.2604	4.31036	214.537	13373.07	.0121
2022	49124.07	232.5957	4.31036	214.537	13512.89	.0119
2023	49625.12	239.1084	4.31036	214.537	13650.72	.0117
2024	50148.08	245.8035	4.31036	214.537	13794.57	.0115
2025	50681.91	252.6859	4.31036	214.537	13941.41	.0114
2026	51221.7	259.7611	4.31036	214.537	14089.9	.0112
2027	51773.64	267.0345	4.31036	214.537	14241.72	.011
2028	52331.86	274.5114	4.31036	214.537	14395.28	.0109
2029	52896.8	282.1978	4.31036	214.537	14550.68	.0107
2030	53472.1	290.0993	4.31036	214.537	14708.93	.0105
2031	54060.84	298.2221	4.31036	214.537	14870.88	.0104
2032	54659.91	306.5723	4.31036	214.537	15035.67	.0101
2033	55273.43	315.1563	4.31036	214.537	15204.43	.01
2034	55892.85	323.9807	4.31036	214.537	15374.82	.0097
2035	56518.25	333.0521	4.31036	214.537	15546.86	.0094
2036	57149.05	342.3776	4.31036	214.537	15720.37	.0091
2037	57790.2	351.9642	4.31036	214.537	15896.74	.0088
2038	58444.8	361.8192	4.31036	214.537	16076.81	.0085
2039	59104.39	371.9501	4.31036	214.537	16258.24	.0082
2040	59771.73	382.3647	4.31036	214.537	16441.81	.0079
2041	60445.75	393.0709	4.31036	214.537	16627.22	.0076
2042	61127.12	404.0769	4.31036	214.537	16814.65	.0073
2043	61816.84	415.3911	4.31036	214.537	17004.37	.007
2044	62511.55	427.022	4.31036	214.537	17195.47	.0067
2045	63211.19	438.9786	4.31036	214.537	17387.93	.0064
2046	63917.93	451.27	4.31036	214.537	17582.33	.0061
2047	64628.21	463.9056	4.31036	214.537	17777.72	.0058
2048	65348.03	476.895	4.31036	214.537	17975.72	.0055
2049	66072.87	490.248	4.31036	214.537	18175.11	.0052
2050	66803.52	503.9749	4.31036	214.537	18376.09	.0049

Table 21: Assumptions for each calendar year

Birth year	Normal Retirement Age	Delayed Retirement Credit
1890	780	.03
1891	780	.03
1892	780	.03
1893	780	.03
1894	780	.03
1895	780	.03
1896	780	.03
1897	780	.03
1898	780	.03
1899	780	.03
1900	780	.03
1901	780	.03
1902	780	.03
1903	780	.03
1904	780	.03
1905	780	.03
1906	780	.03
1907	780	.03
1908	780	.03
1909	780	.03
1910	780	.03
1911	780	.03
1912	780	.03
1913	780	.03
1914	780	.03
1915	780	.03
1916	780	.03
1917	780	.03
1918	780	.03
1919	780	.03
1920	780	.03
1921	780	.03
1922	780	.03
1923	780	.03
1924	780	.03
1925	780	.035
1926	780	.035
1927	780	.04
1928	780	.04
1929	780	.045
1930	780	.045
1931	780	.05
1932	780	.05
1933	780	.055
1934	780	.055
1935	780	.06
1936	780	.06
1937	780	.065
1938	782	.065
1939	784	.07
1940	786	.07
1941	788	.075
1942	790	.075
1943	792	.08
1944	792	.08
1945	792	.08
1946	792	.08
1947	792	.08
1948	792	.08
1949	792	.08
1950	792	.08
1951	792	.08
1952	792	.08
1953	792	.08
1954	792	.08
1955	794	.08
1956	796	.08
1957	798	.08
1958	800	.08
1959	802	.08
1960	804	.08

Table 22: Assumptions for each birth year. In years after 1960, all values are held constant at their 1960 levels.

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