

Appendix B

The Future Elderly Model: Technical Documentation

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1.1 ORIGIN OF THE MODEL

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 (aged 65+). A description of the original model can be found in Goldman et al. (2004). This appendix incorporates information from the original description and from more recent versions of the FEM technical documentation.¹ The original work was funded by the Centers for Medicare & Medicaid Services (CMS) 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. Over time, various extensions have been implemented to the original model, and other individuals have contributed to the technical development of the FEM; we are thankful to Barbara Blaylock, Christine Eibner, Adam Gailey, Laura Gasque, Patricia St. Clair, Igor Vaynman, and Yuhui Zheng for their contributions.

The most recent FEM 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

¹Further information on the FEM, including a description of its historical development, may be found at <http://roybal.healthpolicy.usc.edu/projects/fem.html> [March 2015].

RAND Roybal Center for Health Policy Simulation (grant P30AG024968), the Department of Labor through contract J-9-P-2-0033, the National Institute on 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.

All tables referenced in the following sections are available online. Appendix B and the accompanying Excel workbook are available to download at [nap.edu/Growing Gap](http://nap.edu/Growing_Gap) under the Resources tab.

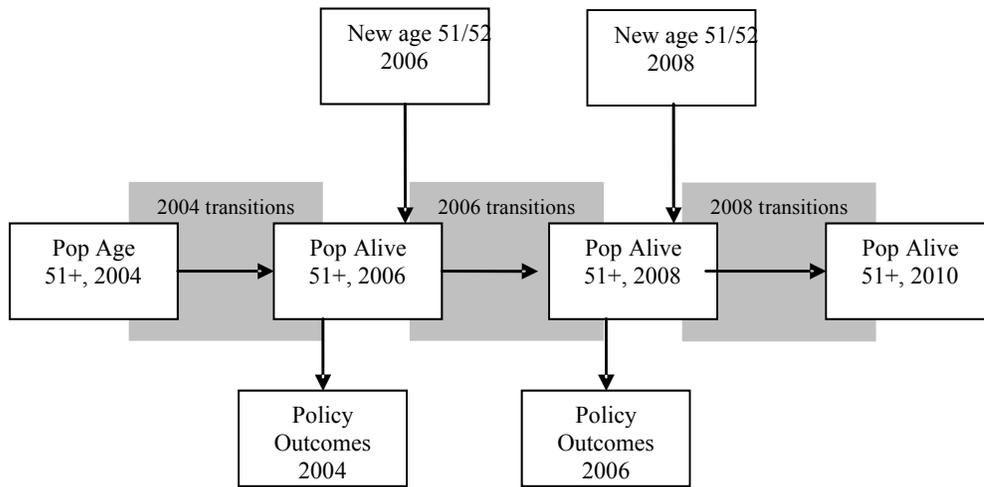
1.2 OVERVIEW OF MODEL ARCHITECTURE

The defining characteristic of the FEM is the modeling of real rather than synthetic cohorts, all of which 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, FEM users 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 some generalizability, but the bulk of expenditure on the public programs the study committee considers in this report occurs after age 50.

The model has three core components:

1. The initial cohort module predicts the economic and health outcomes of new cohorts of 51- and 52-year-olds. This module uses data from the HRS and trends

- calculated from other sources. It allows the model user to "generate" cohorts as the simulation proceeds so that outcomes can be measured for the population aged 51 and older in any given year.
2. 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 HRS.
 3. 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 the study committee had access to HRS-linked restricted data from Social Security records and employer pension plans, the analyses for the report were able to model retirement benefit receipt.



A-1 Architecture of the FEM.

Figure A-1 provides a schematic overview of the FEM as used for the analyses presented in this report. It starts in 2004 with an initial population aged 51 and older, taken from the HRS. It then predicts outcomes using the estimated transition probabilities discussed below in Section 4.1. Those in the cohort who survive to the end of that year are the basis for calculating policy outcomes for the year. The analysis then moves to the following time period (2 years later), when a new cohort of 51- and 52-year-olds enters (see Section 5.1). This entrance forms the new age 51 and older population, which then proceeds through the transition model as before. This process is repeated until the final year of the simulation is reached.

1.3 COMPARISON WITH OTHER PROMINENT MICROSIMULATION MODELS

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.

The Congressional Budget Office Long Term (COBOLT) model uses time-series techniques to project health expenditure growth in the short term and then makes an assumption on long-term growth. For Medicare costs, the Congressional Budget Office use a long-term growth-of-excess-costs with this model of 2.3 percentage points starting in 2020. It then assumes a reduction in excess cost growth in Medicare of 1.5 percent through 2083, leaving a rate of 0.9 percent in 2083. For non-Medicare spending, it assumes an annual decline of 4.5 percent, leading to an excess growth rate in 2083 of 0.1 percent.

For its estimations, CMS performs an extrapolation of medical expenditures over the first 10 years, then computes a general equilibrium model for years 25 through 75 and linearly interpolates to identify medical expenditures in years 11 through 24. The core assumption CMS uses is that excess growth of health expenditures will be one percentage point higher per year for years 25-75 (that is, if nominal growth in gross domestic product [GDP] is 4 percent, health care expenditure growth will be 5 percent).

2. Data Sources for Estimation

The HRS is the main data source for the FEM. For the committee’s analysis, the HRS data were supplemented with merged Social Security covered earnings histories and with data on health trends and health care costs from three major health surveys in the United States. These surveys and the samples selected for the analysis are described below. The variables used in the analysis are listed first, followed by 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	Body Mass Index (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	Hyper-tension	Medicare Part A Expenses
Disability Insurance (DI) Claim	Diabetes	Medicare Part B Expenses
Defined Benefit Claim	Lung Disease	Social Security Outlays
Supplemental Security Income Claim	Nursing Home	
Social Security Claim	Body Mass Index	
	Smoking Status	
	Activities of Daily Living Limitations	
	Instrumental Activities of Daily Living Limitations	

2.1 HEALTH AND RETIREMENT STUDY

HRS interviews occur every 2 years. The HRS waves for 1998-2008 were used to estimate the transition model. The committee used the HRS dataset created by RAND² (version K) as the basis for its analysis. All cohorts in this dataset were used in the analysis. When sampling weights are used, the 2004 HRS is designed to be representative of U.S. households where at least one member is at least 51 years old. For more on HRS sampling weights, see Ofstedal and colleagues (2011). The HRS is also used as the host data for the simulation (population aged 51 and in 2004) and for new cohorts (aged 51

²The RAND HRS dataset is produced and distributed by the University of Michigan with funding from the National Institute on Aging (grant number NIA U01AG009740).

and 52 in 2004). The simulation thus treats the weighted HRS sample data as if it were the age-51-plus U.S. population.

The HRS adds new cohorts every 6 years, with the latest available cohort added in 2004, which is why that wave is used as the base year in this report. When the 2010 data are finalized and released, the FEM will be updated to use the new cohort as its base population.

2.2 SOCIAL SECURITY COVERED EARNINGS FILES

To get information on Social Security entitlements of respondents, the HRS data were matched to the Social Security covered earnings files of 1992, 1993, 1998, and 2004, which provide information on earning histories of respondents as well as their entitlement to future Social Security benefits. We then constructed the Average Indexed Monthly Earnings (AIME), the basis for the determination of benefit levels, from these earning histories. The AIME was constructed by first indexing, using the National Wage Index, to the projected wage level when the respondent turns age 60. If this occurs after 2008, the evolution of the National Wage Index was projected using the average annual rate of change for the past 20 years (2.9% nominal). Then the average of the 35 highest-wage years was taken (if less than 35 years are available, the remaining years were considered to be zero-earning years). This annual amount was then converted to a monthly basis in 2004 dollars using the Consumer Price Index. Quarters of coverage, which determine eligibility for Social Security, are defined as the sum of quarters posted to the file. A worker is eligible for Social Security if he or she has accumulated at least 40 quarters of coverage. A worker accumulates roughly a quarter of coverage for every

\$4,000 of covered earnings up to a maximum of 4 quarters per year. Not all respondents agree to have their record matched. Hence, there is the potential for nonrepresentativeness. However, studies have shown that the extent of nonrepresentativeness is small and that appropriate weighting using HRS weights mostly corrects for this problem (Kapteyn et al., 2006; Michaud et al., 2011).³

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 survey that has been administered every year for several decades. But the survey design has been significantly modified several times. Before 1997, different subgroups of individuals were asked about different sets of chronic conditions; starting in 1997, a selected subsample of the adults has been asked about a complete set of chronic conditions. The survey questions are quite similar to those in the HRS. As a result, for projecting the trends of chronic conditions for future 51- and 52-year-olds, the FEM analyses for this report only use data from 1997 to 2010. A review of survey questions is provided in Excel Table 2. Information on weight and height has been asked every year, whereas information on smoking was asked in selected years before 1997 and annually since then.

³Social Security Administration (SSA) permissions have improved since the study by Kapteyn and colleagues (2006), as the HRS has repeatedly asked respondents for permission to access their SSA records. Kapteyn and colleagues reported that 73.7 percent of men and 76.8 percent of women of the original HRS cohort gave permission to access their records. For that same 1992 cohort, the matching for this report showed that 81.3 percent of men and 83.1 percent of women have given permission to access their SSA earnings records.

2.4 THE MEDICAL EXPENDITURE PANEL SURVEY

The Medical Expenditure Panel Survey (MEPS), which began 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 of the MEPS provides data from individual households and their members, which are supplemented by data from their medical providers. The Household Component collects data from a representative subsample of households drawn from the previous year's NHIS. Since the NHIS does not include the institutionalized population including those in nursing homes, neither does the MEPS; this means that the MEPS can only be used to estimate medical costs for the non-elderly population. Information collected during household interviews includes demographic characteristics, health conditions, health status, use of medical services, sources of medical payments, and body weight and height. Each year the Household Component includes approximately 12,000 households or 34,000 individuals. The sample size for those aged 51-64 is about 4,500 individuals. The MEPS has measures of socioeconomic variables comparable to those in the HRS, including age, race/ethnicity, educational level, census region, and marital status.

2.5 MEDICARE CURRENT BENEFICIARY SURVEY

The MCBS is a nationally representative sample of aged, disabled, and institutionalized Medicare beneficiaries. The MCBS attempts to interview each respondent twelve times over 3 years, regardless of whether he or she resides in the community or 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 oversampled. 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 with a target sample size of 12,000 respondents is introduced, 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.

3. Data Sources for Trends and Baseline Scenario

Two types of trends need to be projected in the FEM for the analyses used in this report. First, it needs to project trends in the incoming cohorts (the future new 51- and 52-year-old individuals). These trends include trends in health and economic outcomes. Second, it needs to project excess aggregate growth in real income and excess growth in health spending.

3.1 DATA FOR TRENDS IN ENTERING COHORTS

The study committee used a number of data sources to compute U.S. trends for this report. First, NHIS data were used for chronic conditions, applying the methodology discussed by Goldman and colleagues (2004). Their 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 the NHIS. For example, a representative sample of age 35 individuals born in 1945 is observed starting in 1980. Their disease patterns are followed in the 1980 and 1981 surveys by selecting those aged 36 in 1981, accounting for mortality, etc.

Information on other trends (e.g., for obesity and smoking) was collected from other studies (Honeycutt et al., 2003; Levy et al., 2005; Poterba et al., 2007a and 2007b; Ruhm, 2007; Mainous et al., 2007). Excel Table 3 presents the sources and Excel Table 4 presents the trends that were used in the baseline scenario. Excel Table 5 presents the prevalence of obesity, hypertension, diabetes, and current smokers in 1978 and 2004, plus

the annual rates of change from 1978 to 2004. For information on how the trends were constructed, see the analysis by Goldman and colleagues (2004).

3.2 DATA FOR OTHER PROJECTIONS

The analysis for this report makes two assumptions relating to real growth in wages and medical costs. First, as is done in the 2009 Social Security Trustees Report intermediate scenario (Board of Trustees, Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds, 2009), it assumes a long-term real increase in wages (earnings) of 1.1 percent per year.⁴ Second, as is done by CMS, it assumes excess real growth in medical costs (that is, additional cost growth above GDP growth) to be 1.5 percent in 2004, reducing linearly to 1 percent in 2033, 0.4 percent in 2053, and -0.2 percent in 2083.

The analysis also used the Affordable Care Act cost growth targets as an optional cap on medical cost growth. The baseline medical spending estimates assume those targets are met. GDP growth in the near term (through 2019) is based on Congressional Budget Office projections, with the Social Security Trustees Old Age, Survivors, and Disability Insurance (OASDI) assumption of 2 percent yearly beyond 2019.

3.3 DEMOGRAPHIC ADJUSTMENTS

The analysis for this report includes two adjustments to the weighting in the HRS to match population counts from the decennial census. First, the HRS sample is post-

⁴The long-run growth in the consumer price index in the intermediate scenario is 2.8 percent and the long-run growth in the national average wage index is 3.9 percent. The long-term increase in wages (earnings) used here is the difference between these numbers.

stratified by 5-year age groups, gender, and race, and sample weights are rebalanced using the 2004 Current Population Survey. That survey is itself matched to the decennial census. Since the analysis only considered the set of respondents with matched Social Security records, deleting those without matched records, this adjustment takes account of selectivity based on age, race, and sex. Selectivity on other dimensions, such as education, is not addressed with this method. The adjustment was made for both new cohort and host datasets.

The second adjustment scales up weights for future new cohorts using 2012 population projections from the Census Bureau. Again, the scaling is by race and gender. The simulation for this report uses the intermediate net migration scenario produced by the Census Bureau.⁵

⁵See https://www.census.gov/population/projections/files/downloadables/NP2012_D4.csv [July 2015].

4. Estimation

This section describes the approach used in the study’s analyses to estimate the transition model, which is the core of the FEM, and the initial cohort model that is used to rejuvenate the model. *Throughout this section and the remainder of the technical appendix, “we” refers to the methodology used with the FEM to produce analyses for this study report.*

4.1 TRANSITION MODEL

The analyses for this report cover a large set of outcomes for which we model transitions. Excel 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.

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

We 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 that the individual-specific component of the hazard can be decomposed into two parts: one time-invariant, the other time-variant. The

time-invariant part is composed of the effect of observed characteristics x_i and permanent unobserved characteristics specific to outcome m , $\eta_{i,m}$. The time-variant part represents the effect of previously diagnosed outcomes $h_{i,j_i-1,-m}$ (that is, the outcomes other than outcome m) on the hazard for m .⁶ We assume an index of the form

$z_{m,j_i} = x_i\beta_m + h_{i,j_i-1,-m}\gamma_m + \eta_{i,m}$. Then the latent component of the hazard can be modeled

as:

$$\begin{aligned} h_{i,j_i,m}^* &= x_i\beta_m + h_{i,j_i-1,-m}\gamma_m + \eta_{i,m} + a_{m,j_i} + \varepsilon_{i,j_i,m}, \\ m &= 1, \dots, M_0, j_i = j_{i0}, \dots, j_{iT_i}, i = 1, \dots, N \end{aligned} \quad (1)$$

We approximate a_{m,j_i} with an age spline. After several specification checks, a node at age 75 appears 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 outcome, conditional on being at risk, is defined as

$$\begin{aligned} h_{i,j_i,m} &= \max(I(h_{i,j_i,m}^* > 0), h_{i,j_i-1,m}) \\ m &= 1, \dots, M_0, j_i = j_{i0}, \dots, j_{iT_i}, i = 1, \dots, N \end{aligned} \quad (2)$$

We consider eight outcomes that are absorbing states. The occurrence of mortality censors observation of other outcomes in a current year. Mortality is recorded from exit interviews.

⁶With some abuse of notation, $j_i - 1$ denotes the previous age at which the respondent was observed.

The analysis places a number of restrictions on how feedback is allowed in the model. Excel Table 7 documents the restrictions placed on the transition model. We also use a set of other controls, a list of which is given in Excel Table 8 along with descriptive statistics. We test the statistical significance of the restrictions on the health transition models (both the economic effect on health and the health effect on health), as shown in Excel Table 9.

We have three other types of outcomes. First, there are binary outcomes that are not an absorbing state. We specify latent indices as in equation 1, above, for these outcomes as well, but the lag dependent outcome also appears as a right-hand side variable in the equation. This allows for state dependence.

Second, there are ordered outcomes. These outcomes are also modeled as in equation 1 but we recognize that the observation rule is a function of unknown thresholds ζ_m . Similar to the binary outcomes, this treatment allows for state dependence by including the lagged outcome on the right-hand side of equation 1.

The third type of outcome we consider includes censored outcomes, earnings, and financial wealth. Earnings are only observed when individuals work. For wealth, there is a non-negligible number of observations with zero and negative wealth. For these, we consider two-part models in which the latent variable is specified as in equation 1, but we model probabilities only when censoring does not occur. In total, we have M outcomes.

The term $\varepsilon_{i,j_i,m}$ is a time-varying shock specific to age j_i . We assume that this shock is normally distributed and uncorrelated across diseases. Unobserved differences η_{im} persist over time and are allowed to be correlated across diseases $m = 1, \dots, M$. We

assume these unobserved differences have a normal distribution with covariance matrix Ω_η .

The parameters $\theta_1 = (\{\beta_m, \gamma_m, \varsigma_m\}_{m=1}^M, \text{vech}(\Omega_\eta))$ can be estimated by maximum simulated likelihood. Given the normality distribution assumption applied to the time-varying unobservable differences, the joint probability of all time intervals until failure, right-censoring, or death conditional on individual frailty is the product of normal univariate probabilities. Since 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 observed from initial age j_{i0} to a last age j_{Ti} , the probability of the observed health history is (omitting the conditioning on covariates for notational simplicity) represented by equation 3:

$$l_i^{-0}(\theta; \eta_i, h_{i,j_{i0}}) = \left[\prod_{m=1}^{M-1} \prod_{j=j_{i1}}^{j_{Ti}} P_{ij,m}(\theta; \eta_i)^{(1-h_{ij-1,m})(1-h_{ij,M})} \right] \times \left[\prod_{j=j_{i1}}^{j_{Ti}} P_{ij,M}(\theta; \eta_i) \right] \quad (3)$$

We make explicit the conditioning on $h_{i,j_{i0}} = (h_{i,j_{i0},0}, \dots, h_{i,j_{i0},M})'$, as we have limited information on outcomes prior to this age.

To obtain the likelihood of the parameters given the observables, unobserved heterogeneity must be integrated out. The complication is that $h_{i,j_{i0},-m}$, the terms for the initial outcomes in each hazard, are not likely to be independent of the common unobserved heterogeneity term that needs to be integrated out. The solution used here is to model the conditional probability distribution $p(\eta_i | h_{i,j_{i0}})$, following Wooldridge

(2000). Implementing this solution amounts to including initial outcomes at each baseline hazard, which is equivalent to the following condition:

$$\begin{aligned}\eta_i &= \Gamma h_{i0} + \alpha_i \\ \alpha_i &\sim N(0, \Omega_\alpha)\end{aligned}$$

Therefore, this approach allows for permanent differences in outcomes due to differences in baseline outcomes. The likelihood contribution for one respondent's sequence is therefore given by equation 4:

$$l_i(\theta; h_{i,j_{i0}}) = \int l_i(\theta; \alpha_i, h_{i,j_{i0}}) dF(\alpha_i) \quad (4)$$

To estimate the model, we make use of maximum simulated likelihood. That is, we replace equation 4 with a simulated counterpart based on R draws from the distribution of α . We then optimize over this simulated likelihood using the BFGS algorithm. Because we could not obtain convergence of the joint estimator, we assumed the distribution of α_i to be degenerate. This assumption yields the simpler estimation problem where each equation can be estimated separately.

Problems in fitting the wealth and earnings distributions are that these distributions have a long left-tail and wealth has some negative values. To address these issues, we use a generalization of the inverse hyperbolic sine transform presented in MacKinnon and Magee (1990). First denote the variable of interest y . The hyperbolic sine transform is

$$y = \sinh(x) = \frac{\exp(y) - \exp(-y)}{2} \quad (5)$$

and the inverse of the hyperbolic sin transform is

$$x = \sinh^{-1}(y) = h(y) = \log(y + (1 + y^2)^{0.5}). \quad (6)$$

The inverse transformation can be generalized by first allowing for a shape parameter θ ,

$$r(y) = h(\theta y) / \theta \quad (7)$$

such that the regression model can be specified as

$$r(y) = x\beta + \varepsilon, \varepsilon \sim N(0, \sigma^2). \quad (8)$$

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

$$g(y) = \frac{h(\theta(y + \omega)) - h(\theta\omega)}{\theta h'(\theta\omega)} \quad (9)$$

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

We specify the regression model in equation 8 in terms of the transformation g in equation 9. The shape parameters can be estimated from the concentrated likelihood for θ, ω . We can then retrieve β, σ by standard ordinary least squares (OLS) methodology.

Upon estimation, we can simulate

$$\tilde{g} = x\hat{\beta} + \sigma\tilde{\eta} \quad (10)$$

where η is a standard normal draw. Given this draw, we can retransform using (9) and (5)

$$h(\theta(y + \omega)) = \theta h'(\theta\omega)\tilde{g} + h(\theta\omega)$$

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

Excel Tables 10 through 14 give parameter estimates for the transition models.

4.2 QUALITY-ADJUSTED LIFE YEARS

As an alternative measure of life expectancy, we computed a quality-adjusted life year (QALY) based on the EQ-5D instrument, a health-related quality-of-life measure. The scoring system for EQ-5D was first developed by Dolan (1997) using a sample from the United Kingdom. Later, a scoring system based on a U.S. sample was generated (Shaw et al., 2005). Since the HRS does not ask the appropriate questions for computing EQ-5D but the MEPS does, we used a crosswalk from the MEPS to the HRS for persons not living in a nursing home. The final OLS regression used to compute QALY in the FEM is shown in Excel Table 28. If a person is living in a nursing home, then an additional 0.10 is subtracted from the computed QALY.

5. Model for New Cohorts

This section first discusses the empirical strategy used for the report's analysis; it then presents the model and estimation results. The model for new cohorts integrates information 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 first need to obtain the outcomes listed in Excel Table 16. Ideally, we need information on

$$f_t(y_{i1}, \dots, y_{iM}) = f_t(y_i) \quad (11)$$

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

Generally, we had good information from published or unpublished sources on trends for some moments of each outcome (for example, a mean or a fraction). That is, we had information on

$$g_{t,m}(y_{i,m}) \quad (12)$$

where $g_{t,m}()$ denotes the marginal probability distribution of outcome m at time t . For example, Christopher Ruhm projected the prevalence of different BMI categories (25-30, 30-35, 35-40, 40 plus) using quantile regression on NHANES data, similar to the work in his 2007 paper (Ruhm, 2007). He restricted the ages of interest and estimated the trend in each of the BMI categories. 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 overweight, 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, $f_{t_0}(y_i)$. We made the assumption that only some part of $f_t(y_i)$ evolves over time. In particular, we modeled the marginal distribution of each outcome allowing for correlation across these marginals. The correlations were assumed to be fixed, whereas the mean of the marginals was allowed to change over time.

5.2 MODEL AND ESTIMATION

Assume the latent model for $y_i^* = (y_{i1}^*, \dots, y_{iM}^*)'$,

$$y_i^* = \mu + \varepsilon_i \tag{13}$$

where ε_i is normally distributed with mean zero and covariance matrix Ω . It is useful to write the model as

$$y_i^* = \mu + L_\Omega \eta_i \tag{14}$$

where L_Ω is a lower triangular matrix such that $L_\Omega L_\Omega' = \Omega$ and $\eta_i = (\eta_{i1}, \dots, \eta_{iM})'$ are standard normal. We observed $y_i = \Gamma(y_i^*)$, which is a non-invertible mapping for a subset of the M outcomes. For example, we had binary, ordered, and censored outcomes for which integration is necessary (see Section 4 for discussion of these outcomes).

Because the mapping is non-invertible, integration had to be performed to calculate the likelihood contributions $L_i(\theta | y_i)$. Integration had to be done over a large number of dimensions. We used maximum simulated likelihood to estimate the parameters of the model. The estimator is given by

$$\theta_{MSL} = \arg \max_{\theta=(\mu, \Omega)} \frac{1}{N} \sum_{i=1}^N \log \frac{1}{R} \sum_{r=1}^R \tilde{\Pr}(y_i | \theta)_r \quad (15)$$

where $\frac{1}{R} \sum_{r=1}^R \tilde{\Pr}(y_i | \theta)_r$ is a consistent estimate of $\tilde{\Pr}(y_i | \theta)$. This estimator is consistent if both N, R tend to infinity. In practice, one can vary R to assess the bias of the estimator for smaller R . It is asymptotically efficient for R/\sqrt{N} tending to infinity.

The vector μ can depend on some variables which have a stable distribution over time 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

$$\mu_i = z_i \beta \quad (16)$$

and the whole analysis is done conditional on z_i .

For binary and ordered outcomes, we fixed $\Omega_{m,m} = 1$, which fixes the scale. Also we fixed 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. Because some of the binary outcomes are rare, we fixed correlations to zero between two outcomes if both fractions were positive and below 10 percent. Furthermore, we fixed to zero the correlation between selected outcomes (e.g., earnings) and their selection indicator. Hence, we considered two-part models for these outcomes.

For exposition, we ordered the observed outcomes as binary, ordered, continuous, and censored. The GHK simulator can be used to simulate $\Pr(y_i | \theta)$.

We then start with the first outcome y_{i1}^* , a discrete outcome, and continue through the following steps.

1. A draw of η_{i1} consistent with observed choice y_{i1} is

$$\tilde{\eta}_{i1} = \Phi^{-1}[\tilde{u}_{i1}\Phi(\frac{\bar{c}_{i1}-\mu_{i1}}{L_{\Omega,11}}) + (1-\tilde{u}_{i1})\Phi(\frac{c_{i1}-\mu_{i1}}{L_{\Omega,11}})] \quad (17)$$

where $\bar{c}_{i1} = \begin{cases} +\infty & \text{if } y_{i1} = 1 \\ 0 & \text{if } y_{i1} = 0 \end{cases}$, $c_{i1} = \begin{cases} 0 & \text{if } y_{i1} = 1 \\ -\infty & \text{if } y_{i1} = 0 \end{cases}$ and \tilde{u}_{i1} is a uniform draw. The

bounds are slightly different for ordered outcomes where thresholds are also estimated. In particular we have

$$\bar{c}_{i1} = \tau_k, \bar{c}_{i1} = \tau_{k-1} \text{ if } y_{i1} = k$$

where τ_k are parameters to be estimated.

2. The probability of that first outcome is $\tilde{\text{Pr}}(y_{i1} | \theta) = \Phi\left(\frac{\bar{c}_{i1} - \mu_i}{L_{\Omega,11}}\right) - \Phi\left(\frac{c_{i1} - \mu_i}{L_{\Omega,11}}\right)$

3. Now a draw of η_{i2} consistent with y_{i2} and the draw $\tilde{\eta}_{i1}$ is given by

$$\tilde{\eta}_{i2} = \Phi^{-1}\left[\tilde{u}_{i2}\Phi\left(\frac{\bar{c}_{i2} - \mu_{i2} - L_{\Omega,21}\tilde{\eta}_{i1}}{L_{\Omega,22}}\right) + (1 - \tilde{u}_{i2})\Phi\left(\frac{c_{i2} - \mu_{i2} - L_{\Omega,21}\tilde{\eta}_{i1}}{L_{\Omega,22}}\right)\right]$$

4. Then the probability is given by

$$\tilde{\text{Pr}}(y_{i1}, y_{i2} | \theta) = \tilde{\text{Pr}}(y_{i1} | \theta) \left[\Phi\left(\frac{\bar{c}_{i2} - \mu_{i2} - L_{\Omega,21}\tilde{\eta}_{i1}}{L_{\Omega,22}}\right) - \Phi\left(\frac{c_{i2} - \mu_{i2} - L_{\Omega,21}\tilde{\eta}_{i1}}{L_{\Omega,22}}\right) \right] \quad (18)$$

5. Cycle through 3 and 4 until end of discrete outcomes. Denote by $m_0 - 1$ the number of discrete outcomes.

6. An error consistent with the first continuous outcome is

$$\tilde{\eta}_{im_0} = \frac{y_{i,m_0} - \mu_{i,m_0} - \sum_{s=1}^{m_0-1} L_{\Omega,m_0,s} \tilde{\eta}_{is}}{L_{\Omega,m_0,m_0}}$$

7. The probability is $\tilde{\text{Pr}}(y_{i,m_0} | \theta) = \frac{1}{L_{\Omega,m_0,m_0}} \phi\left(\frac{y_{i,m_0} - \mu_{i,m_0} - \sum_{s=1}^{m_0-1} L_{\Omega,m_0,s} \tilde{\eta}_{is}}{L_{\Omega,m_0,m_0}}\right)$

8. Hence $\tilde{\text{Pr}}(y_{i1}, \dots, y_{i,m_0} | \theta) = \tilde{\text{Pr}}(y_{i1}, \dots, y_{i,m_0-1} | \theta) \tilde{\text{Pr}}(y_{i,m_0} | \theta)$

9. Cycle through 6 to 8 until reaching $m_1 - 1$, the last continuous outcome.

10. Denote by m_1 the first censored outcome. Denote by y_{ij} the binary outcome that records whether y_{im_1} can be observed. A draw consistent with y_{i,m_1} is given by

$$\tilde{\eta}_{im_1} = \Phi^{-1}[\tilde{u}_{im_1}] \text{ if } y_{ij} = 0$$

and

$$\tilde{\eta}_{im_1} = \frac{y_{i,m_1} - \mu_{i,m_1} - \sum_{s=1}^{m_1-1} L_{\Omega,m_1,s} \tilde{\eta}_{is}}{L_{\Omega,m_1,m_1}} \text{ if } y_{ij} = 1$$

If y_{im_1} is continuous and given by a draw similar to (7) if a binary outcome.

11. The probability is then

$$\tilde{\Pr}(y_{i,m_1} | \theta) = \left[\frac{1}{L_{\Omega,m_1,m_1}} \phi\left(\frac{y_{i,m_1} - \mu_{i,m_1} - \sum_{s=1}^{m_1-1} L_{\Omega,m_1,s} \tilde{\eta}_{is}}{L_{\Omega,m_1,m_1}}\right) \right]^{I(y_{i,j}=1)}$$

for continuous and cumulative normal similar to (8) for discrete.

12. Cycle steps 10-11 until reaching M .

13. Repeat steps 1 through 9 R times and calculate $\frac{1}{R} \sum_{r=1}^R \tilde{\Pr}(y_i | \theta)_r$.

14. Repeat for each $i = 1, \dots, N$.

We used draws from Halton sequences to generate uniform random draws (Train, 2003).

Note that draws $\left\{ \left\{ \left\{ u_{im,r} \right\}_{m=1,\dots,M} \right\}_{r=1,\dots,R} \right\}_{i=1,\dots,N}$ are kept fixed throughout the estimation. For

the first pass, we used 10 draws along each dimension.

Because some parameters are naturally bounded, we reparametrized the problem to guarantee an interior solution. In particular, we parametrize

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

and estimate the $(\delta_{m,m}, \xi_{m,n}, \gamma_k)$ instead of the original parameters. Excel Table 17 gives parameter estimates for the indices; Excel Table 18 gives parameter estimates of the covariance matrix in the outcomes.

The latent model is written as

$$y_i^* = \mu + L_{\Omega} \eta_i$$

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

6. Government Revenue and Expenditures

This section gives a limited overview of how government revenues and expenditures were computed for the study. These functions are based on 2004 rules, but predicted changes in program rules have been included, such as changes based on year of birth (e.g., changes in normal retirement age, NRA).

The discussion covers the following revenues and expenditures:

Revenues	Expenditures
Federal Income Tax	Social Security Retirement benefits
State and City Income Taxes	Social Security DI benefits
Social Security Payroll Tax	SSI
Medicare Payroll Tax	Medical Care Costs

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 their AIME and the age at which benefits are first received. If an individual claims at the NRA (65 for those born prior to 1943, 66 for those born between 1943 and 1957, and 67 thereafter), that individual receives his/her 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 that individual's NRA, the benefit is lower than the PIA. If he retires after the NRA, the benefit is higher.

While an individual is receiving benefits prior to the NRA, benefits are taxed above a certain earnings level at a 50 percent marginal tax rate. After the NRA, benefits are taxed at a 33.3 percent marginal tax rate for earnings above a certain threshold. An individual is eligible for half of a spouse's PIA, properly adjusted for the claiming age, if that amount is higher than his/her own retirement benefit. A surviving spouse is eligible for the deceased spouse's PIA. Since the simulations assume prices are constant, we did not adjust benefits for the cost-of-living adjustment, which usually follows inflation. We did, 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 NRA are eligible for their PIA (no reduction factor) if they are judged disabled (which we take as the predicted outcome of receiving DI) and their earnings are under a cap called the Substantial Gainful Activity limit. This limit was \$9,720 in 2004. We ignore the 9-month trial period over a 5-year window in which the Substantial Gainful Activity limit 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 that are lower than what administrative data indicate. To correct for this self-report bias, we link the HRS with SSA administrative data identifying those receiving SSI. In the linked administrative data, 3.96 percent of the population receives SSI, while only 2.79 percent of the HRS sample reports SSI. We therefore estimate a probit of receiving SSI as a function of self-

reporting social security income, as well as demographic, health, and wealth variables. Excel Table 19 contains the estimates used for the FEM analysis.

The SSI benefit amount is taken from the average monthly benefits found in the 2004 Social Security Administration Annual Statistical Supplement (Social Security Administration, 2005). We assign a monthly benefit of \$450 for persons aged 51 to 64 and receiving SSI, and \$350 for persons aged 65 and older and receiving SSI.

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 four types of individual medical spending. The FEM models total medical spending (medical spending from all payment sources), Medicare spending,⁷ 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 used the 2002-2004 MEPS (n = 14,098) for these regressions for persons not Medicare eligible and the 2002-2004 MCBS (n = 33,231) for spending for those who are eligible for Medicare. Those eligible for Medicare include persons eligible due to age (65+) or disability status. A comparison across these different sources is provided in Excel Table 20.

⁷We estimated annual medical spending paid by specific parts of Medicare (Parts A, B, and D) and sum to get the total Medicare expenditures.

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 at the beginning of the 21st century. Excel Table 20 shows the model estimation results for total, Medicaid, and out-of-pocket spending, while Excel Table 21 shows the model estimation results for the Medicare spending. These estimation results 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 percent of all Medicare enrollees and more than 99 percent of enrollees aged 65 or over were in Medicare Part A; we thus assumed that all persons eligible for Medicare take Part A. We used the 1999-2004 MCBS to model take-up of Medicare Part B for both new enrollees into Medicare and current enrollees without Part B. Estimates are based on a weighted probit regression on various risk factors, demographic variables, 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 was estimated via a probit and used in the first year of simulation to assign initial Part B enrollment status. Estimation results are shown in Excel Table 22. The MCBS data over-represents the portion enrolled in Part B, having a 97 percent enrollment rate in 2004 instead of the 93.5 percent rate given by the Medicare Trustee's Report. In addition to this baseline enrollment probit, we applied an elasticity to premiums of -0.10, based on the literature and on simulation calibration for actual uptake through 2009 (Atherly et al., 2004; Buchmueller, 2006). The premiums were computed

using average Part B costs from the previous time step and the means-testing thresholds established by the Affordable Care Act.

Since both the MEPS and MCBS are known to underpredict medical spending, we applied adjustment factors to the three types of predicted individual medical spending so that in year 2004 the predicted per capita spending in FEM equals the corresponding spending in National Health Expenditure Accounts (NHEA) for two age groups: 55-64 and 65 and over. Excel Table 23 shows how these adjustment factors were determined by using the ratio of expenditures in the NHEA to expenditures predicted in the FEM.

The 2006 MCBS contains data on Medicare Part D. The data give the capitated Part D payment and enrollment. When compared to the summary data presented in the CMS 2007 Trustees' Report (Boards of Trustees, Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Fund, 2007), the per capita cost is comparable between the MCBS and the CMS. However, enrollment is underestimated in the MCBS: 53 percent compared to 64.6 percent according to CMS.

Since only one year of Part D enrollment is available in the MCBS, we estimated a cross-sectional model of Part D enrollment rather than a transition model as with Part B enrollment. We estimated a probit model to link demographics, economic status, current health, and functional status to Part D enrollment; see Excel Tables 24 and 25 for the estimates. To account for both the initial underreporting of Part D enrollment in the MCBS as well as the CMS prediction that Part D enrollment will rise to 75 percent by 2012, the constant in the probit model is increased by 0.56 in 2012 and beyond. The per capita Part D cost in the MCBS matches well with the cost reported from the CMS. An

OLS regression using demographic, current health, and functional status is estimated for Part D costs.

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

6.5 TAXES

The analysis included estimates of federal, state, and city taxes paid at the household level. We also calculated Social Security taxes and Medicare taxes. HRS respondents were linked to their spouse in the HRS simulation. We used the program rules from the Organisation for Economic Co-operation and Development (OECD) (Organisation for Economic Co-operation and Development, 2004). Households have basic and personal deductions based on marital status and age. Couples are assumed to file jointly. Social Security benefits are partially taxed. The amount taxable increases with other income from 50 percent to 85 percent. Low income elderly have access to a special tax credit, and the earned income tax credit is applied for individuals younger than 65. We calculated 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 United States. Since administrative data from the Social Security

Administration cannot be used jointly with geocoded information in the HRS, we applied these hypothetical taxes to all respondents.

At the state level, our analysis uses a basic deduction for each member of the household (\$3,100) and taxable income is taxed at a flat rate of 4 percent. 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 percent. There is 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 calculated taxes paid by the employee for OASDI (which includes Social Security benefits and DI) and Medicare (Medicaid and Medicare). These amounts do not include the equivalent portion paid by the employer. OASDI taxes of 6.2 percent were levied on earnings up to \$97,500 (the 2004 cap), while the Medicare tax (1.45%) is applied to all earnings.

7. Implementation of the FEM

The FEM is implemented in multiple parts. Estimation of the transition, cross sectional, and incoming cohort models is performed in the Stata data analysis and statistical software package. The simulation is implemented in C++.

To match the 2-year structure of the HRS data that we used to estimate the transition models, the FEM simulation proceeds in 2-year increments. The end of each 2-year step is designed to occur on July 1 to allow for easier matching to population forecasts from the Social Security Administration.

A simulation of the FEM begins with a population representative of the U.S. population aged 51 and older in 2004, generated from the HRS. In 2-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 U.S. Census Bureau (2012), stratified by race and age. If incoming cohorts are being used, the new 51- and 52-year-olds are added to the population. The number of new 51- and 52-year-olds added is consistent with estimates from the Census Bureau, stratified by race.

Once the new states have been determined and new 51- and 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 persons who 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 2-year interval. To eliminate uncertainty due

to Monte Carlo decision rules, a simulation is performed multiple times (typically 100) and the mean of each summary variable is calculated across repetitions.

Inputs to a FEM simulation include assumptions about growth in the national Average Wage Index, NRA, 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.

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

8. Validation of the FEM

We perform three validation exercises:

1. Cross-validation
2. External validation
3. External corroboration

Cross-validation is a test of the simulation's internal validity that compares simulated outcomes to actual outcomes; external validation compares model forecasts with actual outcomes from other data sources, and external corroboration compares model forecasts to others' forecasts.

8.1 CROSS-VALIDATION

The cross-validation exercise randomly samples half of the HRS respondents for use in estimating the transition models. The respondents not used for estimation, but who were present in the HRS sample in 1998, are then simulated from 1998 through 2012. Demographic, health, and economic outcomes are compared between the simulated ("FEM") and actual ("HRS") populations. These results are presented in Excel Table 39 for 2000, 2004, 2008, and 2012, with a t-test of the difference between the average values in the two populations.

Worth noting is how the composition of the population changes in this exercise. In 1998, the sample represents those aged 51 and older. Since we follow a fixed cohort,

the age of the population will increase to 65 and older in 2012. This has consequences for some measures, such as claiming DI, in later years where the eligible population shrinks.

Demographics

Demographic differences between the two populations are small. The gender balance and fraction of the population that is non-Hispanic Black is consistent. The difference in average age is 0.3 years in 2012. The FEM population is more Hispanic than the HRS in 2012.

Health Outcomes

The FEM population has a slightly higher population with one or more Activities of Daily Living Limitation in 2012 (19.6% versus 17.5%). Those with any Instrumental Activities of Daily Living Limitations are not statistically different from one another in 2012.

The two populations are not statistically different from each other for prevalence of cancer, hypertension, or lung disease in 2012. They do differ for diabetes (26.8% for the FEM, 25.0% for the HRS), heart disease (35.3% for the FEM, 32.8% for the HRS), and stroke (12.3% for FEM, 11.1% for the HRS), though the practical significance of these differences is not clear.

Health Risk Factors

Average BMI is slightly higher for the FEM population in 2012 (28.0 for the FEM versus 27.7 for the HRS). In terms of practical significance, this difference is equivalent to 2 pounds for an individual who is 5 ft. 8 in. Smoking behavior is not

statistically different between the two populations in 2012. The nursing home population is also not statistically different between the FEM and the HRS.

Economic Outcomes

Federal DI claiming is higher in the HRS than in the FEM in later years of comparison. This measure is restricted to those under age 65, so it does become less precise as the denominator shrinks. Social Security claiming and SSI claiming do not differ between the FEM and the HRS by 2012. The population working is slightly lower in the FEM (22.9% for the FEM versus 24.6% for the HRS).

Household wealth differs in 2012 (\$362,000 for the FEM versus \$339,000 for the HRS). Earnings and capital income do not differ significantly between the two populations.

On the whole, the cross-validation exercise is reassuring. Comparing simulated outcomes to actual outcomes using a set of transition models estimated on a separate population reveals that the majority of outcomes of interest are not statistically different. In cases where they are, the practical difference often is small.

8.2 EXTERNAL VALIDATION

The external validation exercise compares FEM full population simulations beginning in 2004 to external sources. Here we focus on per capita benefits received from Social Security, DI, and SSI, followed by Medicare and Medicaid.

Benefits from the Social Security Administration

Conditional on a simulant receiving benefits, the FEM algorithmically assigns benefits for Old Age and Survivors Insurance (OASI), SSI, and DI. Here, we compare simulation results to SSA figures.

For OASI, we compare to the SSA's December 2012 Monthly Statistical Snapshot (Social Security Administration, 2013). Table 2 of that document indicates that the average OASI monthly benefit was \$1,194. FEM forecasts \$1,182 for the average beneficiary for 2012 (see Excel Table 40).

For SSI we compare to Table 3 of the December 2012 Monthly Statistical Snapshot, focusing on the 65 and older population, as that is the only category that is directly comparable. SSA reports that the average monthly benefit for December of 2012 was \$417 (Social Security Administration, 2013). FEM assigns \$415 to those receiving SSI.

SSA does not report a DI figure that is directly comparable to FEM forecasts. However, SSA reports average DI benefits by age, as well as the number of individuals receiving benefits at each age. This allows us to construct the average benefit for workers aged 51 and older. Based on this calculation, the average disabled worker 51 and older received a benefit of \$1,212 in December of 2012 (Social Security Administration, 2012). Spouses of disabled workers can also receive a benefit (SSA reports a benefit of \$304 for spouses of disabled workers for all ages; Social Security Administration, 2013). The 2012 FEM forecast for the average DI beneficiary, which includes both workers and their spouses, is \$1,102.

For medical spending, we compare FEM forecasts in 2010 to NHEA measures from 2010 (Centers for Medicare and Medicaid Services, 2014), the most recent year for which these data are available. NHEA reports total amounts by age range, which we then convert to per capita measures using the 2010 Census. We focus on the ages 65-84 and age 85-and-over populations, as they are directly comparable to FEM forecasts. We also aggregate the two groups to produce an age 65-and-over average. Data are shown in Excel Table 41. FEM is similar to NHEA for the 65-and-over population for Medicare (\$10,473 for NHEA, \$10,494 for FEM) and total medical spending (\$19,265 for NHEA, \$19,056 for FEM). FEM estimates are higher for Medicaid spending (\$2,141 for NHEA, \$2,818 for FEM).

8.3 EXTERNAL CORROBORATION

Finally, we compare FEM population forecasts to Census Bureau forecasts of the U.S. population. Here, we focus on the full HRS population (51 and older) and those age 65 and older. For this exercise, we begin the simulation in 2004 and simulate the full population through 2050. Population projections are compared to the 2012 Census projections for years 2012 through 2050. FEM population forecasts are always within 2 percent of Census forecasts (Excel Table 42).

9. Alterations of the FEM for this Analysis

9.1 EARNINGS QUINTILES

We classified respondents in the HRS based on their Social Security earnings histories. We constructed an earnings measure similar to Bosworth and Burke (2014): the average of a respondent's nonzero earnings from ages 41 through 50. There are a few subtleties in working with these data. Annual earnings are converted to 2004 dollars using the Average Wage Index. Earnings reported on the earnings history file are capped at the particular year's maximum taxable earnings value and the quarter in which the individual reached the cap. We assume that the earnings persisted through the year and annualize the earnings. For example, a respondent reaching the cap in the first quarter would be assumed to earn four times the cap for the year. For households with two individuals, we divide the total household earnings by the square root of 2 and assign this value to both individuals in the household.

The SSA earnings records file we used begins in 1951. Thus we could only construct the earnings measure for individuals born in 1910 or later. For those individuals unobserved in the earnings records, we imputed the household earnings measure with an OLS model. The regressors are less than high school degree, college degree or more, non-Hispanic Black, Hispanic, single, and birth year. The model is estimated separately by gender. Estimation results are provided in Excel Table 29. This imputation model is used for those born before 1910 and for those who did not allow HRS to access their SSA records. Respondents are then classified into earnings quintiles by birth decade and gender.

9.2 COHORTS FOR SIMULATION

We constructed three synthetic cohorts for simulation purposes: a cohort with characteristics that resemble 51-52 year olds born in 1930; a cohort with characteristics that resemble 51-52 year olds born in 1960; and a cohort with characteristics that might resemble 51-52 year olds born in 1990. The health outcomes we assigned are summarized in Excel Table 30.

1930 Birth Cohort

Using the method described in Section 5, we assigned characteristics to the 1930 birth cohort. Health outcomes (heart disease, diabetes, and hypertension) and risk factors (smoking status and BMI) were assigned to match the distributions observed for 45-55 year olds in the National Health and Nutrition Examination Survey (NHANES) from 1976 to 1980. Household earnings were assigned for all simulants, who were grouped into earnings quintiles by gender.

1960 Birth Cohort

We assigned health characteristics and risk factors to a 1960 birth cohort using the standard FEM method, which uses trends observed in the NHIS and the NHANES or reported in the literature. Household earnings were assigned and simulants were grouped into earnings quintiles.

1990 Birth Cohort

We assigned health characteristics and risk factors to a 1990 birth cohort using the standard FEM method, which extrapolates trends observed in the NHIS and the

NHANES or reported in the literature. For this cohort, the prevalence of diabetes and hypertension at age 50 was assumed to increase, as was obesity. Smoking rates, heart disease, and chronic lung disease were assumed to decrease. Household earnings were assigned and simulants were grouped into earnings quintiles.

9.3 ALTERATIONS TO TRANSITION AND COST MODELS

Mortality

We used a reduced specification for mortality compared to what is typical of the FEM. The 2-year mortality probit is specified as a function of age, a linear time trend, earnings quintile, and quintile-specific linear time trends. The model is fully interacted with gender. In the aggregate, this model produces life expectancy values that are consistent with other forecasts. See Excel Table 31 for model estimates.

In addition to modeling 2-year mortality incidence, we also explored modeling mortality parametrically using a Weibull survival model. With age as the time scale, we adjusted the baseline hazard rate by birth year, earnings quintile, and the interaction of birth year and earnings quintile. Men and women were modeled separately. Simulation results were similar between the two methods, although the Weibull led to longer life expectancies for the highest quintile and shorter for the lowest quintile.

Labor Force and Program Participation

The labor force participation, Social Security OASI claiming, and DI claiming models were specified in ways unique to this project. Briefly, we replaced demographic

variables with earnings quintile, interacted with gender. The lagged states of health-related variables were included in the transition models. Instead of age, we included yearly dummy variables for age relative to NRA to allow policy changes to influence labor force and program participation. See Excel Table 32 for model estimates.

Cost Models

We estimated health expenditure models using the MEPS and MCBS. We imputed earnings quintile for respondents in the MEPS and MCBS using a model estimated on the HRS. This model includes 5-year age category dummy variables, non-Hispanic Black, less than high school, college, single, and widowed. The model is fully interacted by gender. Estimation results are presented in Excel Table 33.

As with mortality, we used reduced-form models for the analysis in this report. Costs were estimated as functions of age, mortality, and earnings quintile. The models are fully interacted by gender. Estimation results are shown in Excel Table 34 (Medicaid eligibility estimated with the MCBS), Excel Table 35 (various measures of medical spending estimated with the MCBS), Excel Table 36 (Medicaid eligibility estimated using the MEPS), and Excel Table 37 (non-Medicare medical spending estimated with the MEPS).

9.4 A MODEL OF CONSUMPTION

We used the RAND version of the HRS Consumption and Activities Mail Survey, a mail-in survey conducted during off-years of the HRS (2001, 2003, 2005, 2007, and 2009) with questions designed to produce measures similar to those from the Consumer

Expenditure Survey. The file reports spending but does not report consumption directly. We used the total spending measure from this file, which includes spending on durable and nondurable goods, excluding automobile purchases. The measure is at the household level, so we divided the expenditures between couples where appropriate. We estimated an OLS model of spending using the 2009 data (2007 data provide similar results) and using age and earnings quintile as predictors, fully interacted by gender. Estimation results are in Excel Table 38.

Our measure of total consumption within the FEM includes predicted total spending plus Medicare and Medicaid benefits received. The impact of policy experiments can then be assessed using this measure for welfare calculations.

References

- Atherly, A., Dowd, B., and Feldman, R. (2004). The effects of benefits, premiums, and health risk on health plan choice in the Medicare program. *Health Services Research, 39*(4), 847-864.
- Board of Trustees, Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds. (2009). *The 2009 Annual Report of the Board of Trustees of the Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds*. Washington, DC: U.S. Government Printing Office.
- Boards of Trustees, Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Fund. (2007). *2007 Annual Report of the Boards of Trustees of the Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds*. Available: <https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/ReportsTrustFunds/downloads/tr2007.pdf> [September 2014].
- Bosworth, B.P., and Burke, K. (2014). *Differential Mortality and Retirement Benefits in the Health and Retirement Study*. Economic Studies at Brookings. Available: http://www.brookings.edu/~media/research/files/papers/2014/04/differential%20mortality%20retirement%20benefits%20bosworth/differential_mortality_retirement_benefits_bosworth_version_2.pdf [July 2014].
- Buchmueller, T. (2006). Price and the health plan choices of retirees. *Journal of Health Economics, 25*, 81-101.
- Centers for Medicare & Medicaid Services. (2014). *Age and Gender Tables*. Available: <http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/Downloads/2010GenderandAgeTables.pdf> [March 2015].
- Dolan P. (1997). Modeling valuations for EuroQol health states. *Medical Care, 35*(11), 1095-1110.
- Goldman, D.P., Hurd, M., Shekelle, P.G., Newberry, S.J., Panis, C.W.A., Shang, B., Bhattacharya, J., Joyce, G.F., and Lakdawalla, D.N. (2004). *Health Status and Medical Treatment of the Future Elderly: Final Report*. Santa Monica, CA: RAND Corporation. Also available: http://www.rand.org/pubs/technical_reports/TR169.html [March 2015].
- Honeycutt, A.A., Boyle, J.P., Broglio, K.R., Thompson, T.J., Hoerger, T.J., Geiss, L.S., and Narayan, K.M. (2003). A dynamic Markov model for forecasting diabetes prevalence in the United States through 2050. *Health Care Management Science, 6*(3), 155-164.

- Kapteyn, A., Michaud, P.-C., Smith, J.P., and van Soest, A. (2006). *Effects of Attrition and Non-Response in the Health and Retirement Study*. RAND Working Paper No. WR-407. Available: http://www.rand.org/pubs/working_papers/WR407.html [February 2015].
- Levy, D.T., Nikolayev, N., and Mumford, E.A. (2005). Recent trends in smoking and the role of public policies: Results from the SimSmoke Tobacco Control Policy Simulation Model. *Addiction*, 10, 1526-1537.
- MacKinnon, J.G., and Magee, L. (1990). Transforming the dependent variable in regression models. *International Economic Review*, 31(2), 315-339.
- Mainous, A.G., Baker, R., Koopman, R.J., Saxena, S., Diaz, V.A., Everett, C.J., and Majeed, A. (2007). Impact of the population at risk of diabetes on projections of diabetes burden in the United States: An epidemic on the way. *Diabetologia*, 50(5), 934-940.
- Michaud, P.-C., Kapteyn, A., Smith, J.P., and van Soest, A. (2011). The effects of attrition and non-response in the Health and Retirement Study. *Longitudinal and Life Course Studies*, 2(2), 145-169.
- Ofstedal, M.B., Weir, D.R., Chen, K.T., and Wagner, J. (2011). *Updates to HRS Sample Weights*. *HRS Documentation Report*. Available: <http://hrsonline.isr.umich.edu/sitedocs/userg/dr-013.pdf> [March 2015].
- Organisation for Economic Co-operation and Development. (2004). *Taxing Wages*. Available: http://www.oecd-ilibrary.org/taxation/taxing-wages-2004_tax_wages-2004-en [September 2014].
- Poterba, J., Venti, S., and Wise, D.A. (2007a). *New Estimates of the Future Path of 401(k) Assets*. NBER Working Paper No. 13083. Cambridge, MA: National Bureau of Economic Research.
- Poterba, J., Venti, S., and Wise, D.A. (2007b). *The Decline of Defined Benefit Retirement Plans and Asset Flows*. NBER Working Paper No. 12834. Cambridge, MA: National Bureau of Economic Research.
- Ruhm, C. (2007). Current and future prevalence of obesity and severe obesity in the United States. *Forum for Health Economics and Policy*, 10(2), 1-26.
- Shaw, J.W., Johnson, J.A., and Coons, S.J. (2005). U.S. valuation of the EQ-5D health states: Development and testing of the D1 valuation model. *Medical Care*, 43(3), 203-220.

- Social Security Administration. (2005). *Annual Statistical Supplement, 2004*. Available: <http://www.ssa.gov/policy/docs/statcomps/supplement/2004/> [September 2014].
- Social Security Administration. (2012). *Disabled Worker Beneficiaries Distributed by Age*. Available: http://www.ssa.gov/OACT/ProgData/benefits/da_age201212.html [March 2015].
- Social Security Administration. (2013). *Monthly Statistical Snapshot, December 2012*. Available: http://www.ssa.gov/policy/docs/quickfacts/stat_snapshot/2012-12.pdf [March 2015].
- Train, K. (2003). *Discrete Choice Methods with Simulation*. Cambridge: Cambridge University Press.
- U.S. Census Bureau. (2012). *National Population Projections 2012*. Available: http://www.census.gov/population/projections/files/downloadables/NP2012_D1.csv [March 2015]
- Wooldridge, J.M. (2000). A framework for estimating dynamic, unobserved effects panel data models with possible feedback to future explanatory variables. *Economics Letters*, 68(3), 245-250.