The long-term benefits of increased aspirin use by at-risk Americans aged 50 and older

Technical Documentation

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Introduction

The first section of this document applies specifically to the article "The long-term benefits of increased aspirin use by at-risk Americans aged 50 and older". It expands upon the Methods section of the article in greater detail. The remainder of the document consists of a detailed technical appendix for the Future Elderly Model, the engine used to conduct simulations.

1 Simulating the impact of extended aspirin use

We conduct simulations using the Future Elderly Model (FEM), a dynamic microsimulation model developed by Goldman *et al.* (2004) to forecast the implications of different medical technology scenarios on long-term health and health care spending. The FEM follows Americans aged 51 and older and projects their health and medical spending over time. Its unique feature is to follow the evolution of individual-level health trajectories, rather than the average or aggregate health characteristics of a cohort. In the recent past, researchers have used it for a variety of purposes, including forecasting the changing health status of the elderly Medicare population in the decades 2010-2030 (Gaudette, Tysinger, Cassil, & Goldman, 2015); estimating the impact of the introduction of statin medication on the costs of obesity (Gaudette, Goldman, Messali, & Sood, 2015); and estimating the value of medical interventions to reduce obesity prevalence (P. C. Michaud, Goldman, Lakdawalla, Zheng, & Gailey, 2012); to delay Alzheimer's disease (Zissimopoulos, Crimmins, & St.Clair, 2015); and to delay the biology of aging (D. P. Goldman et al., 2013; Dana P. Goldman, Gaudette, & Cheng, 2016).

The FEM simulates the lives of older Americans using the Health and Retirement Study, a biennial survey of the American population aged 51 and over that has been ongoing since 1992. The Health and Retirement Study data are used to compute the health transition models at the core of the FEM and the input population that goes into the simulations. Health and Retirement Study data are supplemented by the Medical Expenditure Panel Survey, a set of large-scale surveys of the non-institutionalized U.S. population, and the Medicare Current Beneficiary Survey, a nationally representative survey of Medicare beneficiaries, to project health care spending and assess quality of life during the simulations. For each individual, the FEM takes into account initial demographic characteristics and health conditions to project medical spending, health conditions and behaviors, disability status, and quality of life. We describe the model and methods briefly here; details on the modeling are presented in Sections 2 to 8.

The FEM has three core modules, as illustrated in Figure 1. The first module is the Health Transitions module that calculates transition probabilities across various health states based on the individual's current characteristics. Health transitions include chronic disease incidence, functional status, body-mass index, and mortality. These transition probabilities are modeled using first-order Markov processes that depend on a battery of predictors: age, sex, education, race, ethnicity, body-mass index, smoking behavior, marital status, employment, functional status, and health conditions. We also control for baseline factors using a series of initial health variables.

Figure 1 Structure of the Future Elderly Model

Health conditions are derived from Health and Retirement Study survey questions and include diabetes, high blood pressure, heart disease, cancer (except skin cancer), stroke or transient ischemic attack, and lung disease (either or both chronic bronchitis and emphysema). Transitions into illness and death are synthesized in Figure 2. The concept of chronic conditions used in the simulations corresponds to having *ever* been diagnosed with a condition. We thus treat chronic conditions as absorbing: once individuals receive a diagnosis, they are henceforth considered to have that condition.¹ The body-mass index variable is based on the self-reported height and weight of Health and Retirement Study respondents, and its evolution is projected with the estimates of a log-linear model. Functional status is measured by limitations in instrumental activities of daily living or activities of daily living, and residence in a nursing home. The instrumental activities of daily living limitations indicator is based on questions about difficulty using the phone, managing money, and taking medications. The activities of daily living limitations indicator is based on respondents' assessment of their ability to conduct basic tasks, such as dressing, eating, and bathing. For the purpose of this study, we consider individuals free of disability if they reported no limitations and did not live in a nursing home, and as disabled if they reported at least one limitation or lived in a nursing home. Unlike health conditions, we allow for transitions in and out of functional states.

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¹ This interpretation is consistent with the Health and Retirement Study questionnaire, which asks respondents if they were ever diagnosed with a condition.

To evaluate quality of life, we predict quality-adjusted life-years using the EQ-5D, a commonly used quality-of-life index based on five health-related variables addressing mobility, daily activities, self-care, anxiety, depression, and pain. Using the Medical Expenditure Panel Survey data, we apply an ordinary least squares regression to fit derived EQ-5D quality adjustment scores as a function of the chronic conditions and functional states included in the FEM simulations. This model is then used to predict the quality of each person's life-years in our simulations.

Based on two complementary medical spending data sources, the Policy Outcomes module predicts an individual's health spending with regards to health status (chronic conditions and functional status), demographics (age, sex, race, ethnicity, and education), nursing home status, and mortality. Our definition of medical spending includes medical provider visits, hospital events, inpatient stays, outpatient visits, emergency department visits, dental care, home health care, optometry, other medical equipment and services, prescribed medicines, and nursing home stay. Our estimates are based on spending data from the 2007-2010 Medical Expenditure Panel Survey for individuals younger than 65 and the 2007-2010 Medicare Current Beneficiary Survey for individuals aged 65 and older. The estimates are based on pooled least squares regressions of each type of spending on risk factors, self-reported conditions, and functional status, with spending inflated to current dollars using the medical component of the consumer price index.

Finally, the Replenishing Cohorts module, shown at the top of Figure 1, predicts economic and health outcomes of new cohorts of 51-year-olds. This module primarily uses data from the Health and Retirement Study and incorporates trends in demography, disease, body-mass index, smoking, and pensions from the National Health and Nutrition Examination Survey (NHANES), the National Health Interview Survey, and the American Community Survey. This module generates cohorts as the simulation proceeds, so that we can measure outcomes for the age 51-plus population in any given year.

1.1 Simulations overview

In this study, we conduct two types of simulations. The first type is cohort simulations, in which we turn off the Replenishing Cohorts module and follow cohorts of Americans until death under alternative aspirin take-up scenarios. These simulations focus on a representative cohort of Americans aged 51 to 52 in 2010. In each period,² the Policy Outcomes module predicts medical expenditure on the person's current-state vector. Then, the Health Transitions module predicts survival, health transitions, gastrointestinal bleeding, functional status, and quality-adjusted life-years for the next period, using the FEM's transition probabilities. The same process is repeated at each time step until everyone in the cohort has died. These simulations are useful to compare expected lifetime outcomes across scenarios, such as the probability of contracting a disease by a given age, life expectancy, and lifetime medical spending.

The second type consists of population simulations, in which we use the full FEM structure to project outcomes for the entire American population aged 51 and older until year 2050. In each period, individual outcomes are aggregated to reflect population health measures, such as disease prevalence and aggregate medical costs.

Scenarios

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We consider two main scenarios:

- The **Guideline Adherence** scenario provides the health benefits and side effects of aspirin to all individuals for whom aspirin is recommended by the US Preventive Services Task Force and American Heart Association guidelines. We consider the guidelines that were effective at the time of the 2011-2012 NHANES survey on aspirin use. With regard to primary prevention therapy, these guidelines specify a series of 10-year of coronary heart disease and stroke risk thresholds over which men and women are eligible for daily aspirin use as a primary prevention therapy (US Preventive Services Task Force, 2009). With regard to secondary prevention therapy, this scenario considers individuals with a prior stroke or cardiovascular disease as eligible for daily aspirin, as specified by the American Heart Association and American College of Cardiology Foundation guidelines (Smith et al., 2011).³ Comparisons between the baseline FEM projections (Status Quo scenario) and this scenario will illustrate the full potential of the guidelines, as well as the foregone benefits because of low aspirin use.
- The **Universal Eligibility** scenario provides the health effects of aspirin to all Americans aged 51 and older. This scenario aims to provide an *upper bound* of the impact of additional aspirin use for the U.S. elderly, rather than a realistic

² Since the Health and Retirement Study is biennial, we simulate health and costs over two-year periods.

 3 Guidelines for secondary prevention therapy and risk reduction produced by the American Heart Association and American College of Cardiology Foundation broadly define secondary prevention patients as "patients with established coronary and other atherosclerotic vascular disease, including peripheral artery disease, atherosclerotic aortic disease, and carotid artery disease." The most recent update to the secondary prevention guidelines specifically recommends using aspirin 75-162 mg daily in all patients with coronary artery disease unless contraindicated, as well as Aspirin alone (75-325 mg daily), clopidogrel alone (75 mg daily), or combination aspirin plus extended-release dipyridamole in all patients with extracranial or vertebral atherosclerosis who have had ischemic stroke or transient ischemic attack.

assessment of the impact that would occur if everyone aged 51 and older used aspirin daily.

1.2 Eligibility

Scenarios are implemented in two steps. First, we identify the individuals affected by the scenario. Since a subset of the population eligible for aspirin already takes the medication, we identify in FEM simulations individuals admissible for aspirin use under each scenario but *not* using aspirin. These are the individuals who would see their life outcomes change if the guidelines were fully observed or if all Americans aged 51 and older started taking aspirin. Since there is no Health and Retirement Study question about aspirin use, we turn to NHANES data, which contain detailed information about clinical bio-markers and aspirin use.

The NHANES data reveal a large unmet need for daily aspirin. In the article's Figure 1, we compare the population eligible for aspirin in a primary or secondary prevention setting against its reported aspirin use. Primary prevention eligibility, which corresponds to 10-year risks of coronary heart disease and stroke above the thresholds of the guidelines, is shown in yellow; secondary prevention eligibility, which corresponds to the population with a prior stroke or heart disease, is shown in blue. The darker section of the bars shows the proportion of the eligible population that also reported using daily aspirin.

Strikingly, most men aged 50 to 69 presented coronary heart disease risks above the risks for which aspirin use was recommended, but less than 20% were following the guidelines (in pale yellow). Fewer women presented a risk of stroke above the thresholds recommended for aspirin use, but over 10% of women in all age groups over 55 were eligible for aspirin use but not taking it. The data used to estimate this population and the process to identify it in FEM simulations are detailed in following section.

1.2.1 Data

To estimate the probability that individuals are eligible for aspirin use within FEM simulations, we utilize estimates based on the National Health and Nutrition Examination Survey (NHANES) data. NHANES is a set of studies combining interviews and physical examinations to assess the health and nutritional status of adults and children in the United States.

In this study, we assemble and use several components of NHANES to assign aspirin eligibility. Demographic files and medical conditions files are used to extract characteristics of respondents common to both NHANES and the FEM (which is based on the Health and Retirement Study). Second, information from biomarker measurements¬—namely cholesterol and blood pressure—are used to calculate 10-year risks of coronary heart disease and stroke. Comparing these risks against the US Preventive Services Task Force's (USPSTF) 2009 guidelines' thresholds provides the eligibility for aspirin use. Finally, this study benefits from a special survey on the preventive use of low-dose aspirin conducted in 2011-2012.

By bringing in components together for years 2007-2012, we obtained an individual-level database including individual characteristics, risk of cardiovascular events, and daily aspirin use in 2011-2012. A NHANES respondent is defined as an aspirin We define as an aspirin user a respondent of the NHANES 2011-2012 preventive

aspirin use questionnaire if he or she self-reported taking daily low-dose aspirin as advised by a doctor of other health care provider; or if he or she self-reported as taking daily low-dose aspirin on his or her own.

Under the Guideline Adherence scenario that we implement in FEM, we define the eligibility for aspirin use in a primary prevention context as the intersection of 1) not using low-dose aspirin, and 2) displaying a risk for coronary heart disease and stroke events above the thresholds of the 2009 USPSTF guidelines. Since both outcomes are dichotomous, we conduct probit regressions on our NHANES dataset to find the probability that individuals are eligible at each period in the FEM simulations.

1.2.2 Estimation

The first regression finds the factors influencing the probability that individuals aged 51 and over (the population covered by the FEM) declare using daily low-dose aspirin, based on information common to NHANES and the FEM: demographics, education, health conditions and body-mass index. The second sets of regressions find the factors influencing the probability of women (men) having a risk of stroke (coronary heart disease) above the USPSTF thresholds, respectively. Since the guidelines concern the primary prevention of cardiovascular diseases and target men aged 45-79 and women aged 55-79, we apply the same restrictions to these regressions' samples. Additionally, the USPSTF guidelines statement specifies that all diabetic men are eligible for daily aspirin use, therefore they are excluded from the regression.

After several specification checks, we used age splines with nodes at age 59 and 69 in the models for aspirin use and eligibility for primary prevention aspirin use in men to maximize fit. For women age and age-squared variables produced a better fit than age splines and were favored. The results of these regressions are presented in tables 1 and 2.

1.2.3 Assignment and validation

The use of these estimates follows the same methodology as the other nonabsorbing binary outcomes in the FEM. At the end of each two-year period, we assign aspirin use and Guideline Adherence eligibility to each simulated individuals based on their characteristics and the models presented in tables 1 and 2. In the Guideline Adherence scenario, individuals for whom the simulations indicate that they do not currently use aspirin and have a risk superior to the thresholds suggested by the USPSTF are defined as eligible. Additionally, all diabetic men under age 80 are considered eligible. These constitute the population eligible for daily use of aspirin in a primary prevention setting. Additionally, all individuals with a prior diagnosis of stroke or cardiovascular disease are considered eligible for daily aspirin use in a secondary prevention setting.

Thus, NHANES data is used to assign aspirin eligibility to our FEM populations, which are based on Health and Retirement Study data. The two surveys are representative of the American population they study, but whether our assignment of aspirin intervention eligibility will be consistent with observed data is initially unclear. To verify this, we impute eligibility for aspirin as a primary prevention therapy to each individual of the FEM sample used for population simulations. We then compare the population

identified as eligible for an aspirin intervention to its observed counterpart in NHANES in wave 2011-2012 (Table 3).

We find that our imputation models identify a somewhat smaller proportion of the population as eligible for an aspirin intervention relative to the NHANES data. Also, the population identified by the imputation presents superior health indicators: it is less likely to be obese, currently smoking, or hypertensive. These discrepancies suggest that the imputation leads to conservative estimates of the true population that could benefit from aspirin therapy and of the health benefits they obtain from the intervention.

*** p<0.01, ** p<0.05, * p<0.1. BMI refers to "body mass index", defined as the ratio between mass of individuals, expressed in kilograms, and the square of height, expressed in meters. A respondent of the NHANES 2011-2012 preventive aspirin use questionnaire respondent is defined as an aspirin user if he or she self-reported taking daily lowdose aspirin as advised by a doctor of other health care provider; or if he or she self-reported as taking daily low-dose aspirin on his or her own.

Table 2 Factors Influencing the Probability of Eligibility for Primary Prevention Aspirin Use in NHANES, 2007-2012: Probit Estimates

*** p<0.01, ** p<0.05, * p<0.1. BMI refers to "body mass index", defined as the ratio between mass of individuals, expressed in kilograms, and the square of height, expressed in meters. Eligibility for primary prevention daily use of aspirin is assigned to NHANES respondents based on 2009 USPSTF guidelines and established 10-year risk calculators for coronary heart disease and stroke.

Table 3 Comparison of Population Identified as Eligible for Aspirin Intervention in FEM Simulations and NHANES Data

*Eligibility for primary prevention daily use of aspirin is assigned to respondents based on USPSTF thresholds and established 10-year risk calculators for coronary heart disease and stroke and aspirin use. "NHANES" refers to author's calculations with the 2011-2012 wave of the NHANES. "FEM" refers to the imputation of aspirin eligibility in the Future Elderly Model's stock population using the models shown in Tables 1 and 2.

1.3 Health Impact and Costs of Aspirin

The second step modifies health transitions and outcomes of eligible individuals to reflect the health impact of aspirin use reported by the clinical trials literature. These include both health benefits of daily aspirin use and its side effects, both of which have been reported by many researchers. Table 4 summarizes the most important findings from recent meta-analyses.

For eligible individuals, we decrease the probabilities of contracting heart disease, experiencing a stroke, and mortality and increase the risks of gastrointestinal bleeding. We incorporate differential effects by sex and context:

- 1. **Heart disease:** For individuals who have never been diagnosed with a cardiovascular disease (i.e. in a primary prevention setting), we decrease the probability of contracting heart disease by factors with a mean of 0.90. The distribution used corresponds to the risk ratios of total cardiovascular disease events among the primary prevention population reported by Seshasai *et al.* (2012). For individuals with a prior stroke but no history of other heart disease, we decrease the probability of contracting a heart disease by factors with a mean of 0.79, based on Berger *et al.* (2008).
- 2. **Stroke:** A meta-analysis conducted in 2006 by Berger revealed differential effects of aspirin by stroke type and sex in individuals with no prior cardiovascular disease. For men, this study reported that daily aspirin use does not significantly reduce the risk of ischemic stroke but *increases* the risk of hemorrhagic stroke. For women, however, aspirin reduces the ischemic stroke risk and does not significantly increase hemorrhagic stroke risk. Since the concept of stroke in the Health and Retirement Study includes both types, we implement the total stroke effects reported by the same study: we modify the

overall risk of stroke for men and women by factors with a mean of 1.13 and 0.83, respectively. In a secondary prevention setting, we reduce the risk of stroke of both men and women by factors with a mean of 0.75, based on Berger *et al.* (2008).

- 3. **Cancer:** While no comprehensive meta-analysis of the impact of aspirin on cancer exists yet, strong evidence suggests a causal reduction of the incidence of several cancers due to aspirin therapy. Table 5 weights best and conservative estimates of risk ratios for several cancers' incidence published in a recent review of existing clinical trials, cohort studies, and case-control studies (Cuzick et al., 2014) against the relative incidence of these cancers in the Health and Retirement Study. We reduce the incidence probability of cancer by 0.94, which corresponds to the conservative estimates.
- 4. **Mortality:** Depending on whether aspirin is used for primary or secondary prevention, the literature reports differential mortality effects of aspirin. In a primary prevention setting, we modify mortality probability by factors with a mean of 0.94, based on the estimates reported by Seshasai et al. (2012).⁴ In a secondary prevention setting, we decrease the mortality probability by factors with a mean of 0.87, based on Berger *et al.* (2008). In the simulations, the parameters are adjusted for the indirect impact of aspirin on mortality through its prevention of non-fatal chronic disease incidence, which impact the probability of mortality in subsequent periods. The adjustment is obtained by conducting intermediary cohort simulations in which aspirin is allowed to impact heart disease, stroke, and cancer, but not mortality, and then comparing the ratio of mortality rates in this scenario to the baseline. Specifically, participants of the studies comprising the Berger *et al.* (2008) meta-analysis had a mean age of 63.9 at baseline and were followed for an average of 33 months, over which aspirin use was associated with an all-cause mortality risk ratio point estimate of 0.87. With FEM, we allowed aspirin to impact incidence of chronic disease but not mortality at ages 63 to 67 in a secondary prevention setting. This exercise resulted in an all-cause mortality ratio with the status quo of 0.998 over these ages. We thus applied a reduction of mortality using factors with a mean of $0.87/0.998 = 0.872$. Similarly, participants of the studies comprising Seshasai *et al.* (2012) had a mean age of 57 at baseline and were followed for an average of 6 years. Allowing aspirin to impact incidence of chronic disease and mortality in a secondary prevention setting but not of mortality in a primary prevention setting resulted in an all-cause mortality ratio of 0.984 at ages 57 to 63. We thus modify mortality probabilities using factors with a mean of $0.94/0.984 = 0.955$.
- 5. **Gastrointestinal bleeding**: Gastrointestinal bleeding is the most common side effect of daily aspirin use. Based on the estimates of McQuaid and Laine (2006), we increase bleeding risk by factors with a mean of 1.73, which are consistent with low-dose daily use of aspirin (75 to 162.5 mg/day). To introduce the baseline bleeding risks in the FEM to which the factors are

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⁴ We note that a recent large-scale randomized study conducted in Japan, which has not yet been included in meta-analyses, did not find a reduction in all-cause mortality in a primary care setting (Ikeda et al., 2014). We therefore conduct a sensitivity scenario in which we remove this parameter.

applied, we use the age- and gender-stratified rates of any gastrointestinal bleeding events in the UK general population risks reported by Thorat and Cuzick (2015). ⁵ Following estimates from the medical literature on bleeds, we impose a utility adjustment of 0.125^6 and a medical cost of \$4,639⁷ for additional gastrointestinal bleeding incidents incurred because of aspirin use (Campbell et al., 2015; Ghate, Biskupiak, Ye, Kwong, & Brixner, 2011).

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 5 The authors estimate that about 10% of gastrointestinal bleeding events in the population were due to the use of nonsteroidal anti-inflammatory drugs, of which aspirin is a prominent member. To correctly reflect the risks of individuals prior to using aspirin, we thus consider .9 times the incidence rates as the baseline risks of gastrointestinal bleeding.

⁶ Campbell *et al.* find that upper gastrointestinal bleeding is associated with a mean EQ-5D health-related quality-of-life score among survivors of 0.735 at 28 days, in comparison with a general population score of 0.86. In our simulations, this quality-of-life decrement is applied as a reduction of 0.125 to QALY scores predicted by the FEM in the whole year in which a gastrointestinal bleed occurs.

⁷ Ghate *et al.* used generalized linear regression to model health care costs during the 12 months after a warfarin prescription among patients using warfarin to prevent occlusive stroke secondary to atrial fibrillation. They compared health care costs between those patients that had a bleeding event within the first 30 days following their warfarin claim and those that did not. The models adjusted for age, gender, region, insurance plan type, and comorbidity. Assuming that the difference in costs between the "no bleeding" group and the "major GI" group is entirely attributable to the gastrointestinal bleed, then the gastrointestinal bleed resulted in \$13,747 in combined inpatient and outpatient costs over 12 months, after adjusting for the previously mentioned factors. Minor gastrointestinal bleeds, which accounted for 66.3% of gastrointestinal bleeding events, did not increase annual costs significantly. The value used in our simulation corresponds to the costs of major gastrointestinal bleeds weighted by their relative occurrence.

Table 4 Health Impact of Aspirin Reported by Large Meta-Analyses

Findings used in the simulations are shown in bold font. Only statistically significant findings are shown, with the exception of non-statistically significant findings that were included in the simulations. RR - risk ratio, OR - odds ratio, CVD - cardiovascular disease, MI - myocardial infarction, GI – gastrointestinal.

Table 5 Potential for aspirin to reduce cancer incidence in the population aged over 50

*: Corresponds to the share of new incident cancers observed in Health and Retirement Study at ages over 50 (years 1995-2008). "Incident" means that the respondent reported no cancer in the prior wave, but reported cancer in reference wave; **: Site-specific risk ratio estimates of Cuzick *et al*.(2014).

Finally, we take into account the direct purchasing cost of aspirin medication. As mentioned in the introduction, aspirin is quite inexpensive. As of the writing of this article, the estimated cost of providing a patient with a daily low-dose aspirin tablet would range from less than \$5 to about \$20 per year, depending on the seller and brand. In our simulation, we opt for a measure of \$7.29, based on a unit cost of \$0.019 per 81mg tablet. ⁸ As shown in the results section, the direct cost of aspirin is minimal in comparison with its health impact and health care spending consequences.

1.4 Uncertainty

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To account for documented uncertainty in the health impact of aspirin, we sampled estimates of its clinical effect from the confidence intervals for relative risks reported by the literature.⁹ Assuming parameters to be independent from each other, we drew 200 sets of risk-ratio estimates from a log-normal distribution and conducted separate simulations for each of them. We then computed and sorted the simulation results for all variables of interest. In the remainder of the article, the point estimates of our results correspond to the mean of each variable of interest across the 200 draws. The bounds of the 95%

⁸ This cost corresponds to the 500-count package price for Walgreens brand aspirin found on the website www.drugstore.com on March 2, 2015.

⁹ This random sampling excludes cancer factors, for which Cuzick *et al.* did not produce confidence intervals.

confidence intervals correspond to the $5th$ lowest and highest results for each variable of interest. These intervals can be interpreted as simulated 95% confidence intervals with regard to the clinical uncertainty of the effectiveness of aspirin.

2 Functioning of the Dynamic Model

2.1 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 versions 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.

All tables referenced in the following sections are shown at the end of the document.

2.2 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 provides a schematic overview of the model. We start in 2014 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.

2.3 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.

2.3.1 CBOLT Model (CBO)

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%.

2.3.2 Centers for Medicare and Medicaid Services (CMS)

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%).

3 Data Sources 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

Estimated Outcomes in/from Transition Model

3.1 Health and Retirement Study

The Health and Retirement Study (HRS), waves 1992-2004 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.

3.2 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 and 2004 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 to 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 nonrepresentativeness. However, recent studies show that the extent of nonrepresentativeness is quite small and that appropriate weighting using HRS weights mostly corrects for this problem (P.-C. Michaud, Kapteyn, Smith, & van Soest, 2006).

3.3 National Health Interview Survey (NHIS)

The NHIS contains individual-level data on height, weight, smoking status, self-reported chronic conditions, income, education, and demographic variables. It is a repeated crosssection 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.

3.4 The Medical Expenditure Panel Survey (MEPS)

The 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 nonelderly 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.

3.5 Medicare Current Beneficiary Survey (MCBS)

The 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.

4 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.

4.1 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 (D. 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; Mainous et al., 2007; Poterba, Venti, & Wise, 2007a, 2007b; Ruhm, 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.

4.2 Data for Other Projections

We make two assumptions relating to real growth in wages and medical costs. Firstly, as is done in the social security trustees report intermediate scenario, we assume a long term real increase in wages (earnings) of 1.1% per year. As is done by 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.

4.3 Demographic Adjustments

We make two adjustments to the weighting in the Health and Retirement Study to match population counts from the Census. First, we post-stratify the HRS sample by 5 year age groups, gender and race and rebalance weights using the 2004 Current Population Survey (CPS). The CPS is itself matched to the decennial Census. 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. We do this for both new cohort and host data set. The second adjustment we make is to scale up weights for future new cohorts using population projections from the Census Bureau. Again, we do this by race and gender. We use the intermediate net migration scenario produced by SSA in our simulation.

5 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 model.

5.1 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 $j_i = j_{i0},..., j_{iT_i}$.

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 and permanent unobserved characteristics specific to outcome m , $h_{i,m}$. The time-varying part is the effect of previously diagnosed outcomes $h_{i,j_{i-1,-m}}$, (outcomes other than the outcome *m*) on the hazard for m.¹⁰ We assume an index of the form $z_{m,j_i} = x_i b_m + h_{i,j_i-1,-m} g_m + h_{i,m}$. Hence, the latent component of the hazard is modeled as

$$
h_{i,j_i,m}^* = x_i b_m + h_{i,j_i-1,-m} g_m + h_{i,m} + a_{m,j_i} + e_{i,j_i,m},
$$

\n
$$
m = 1,..., M_0, j_i = j_{i0},..., j_{iT_i}, i = 1,..., N
$$
\n(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

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

\n
$$
m = 1, ..., M_0, j_i = j_{i0}, ..., j_{iT_i}, i = 1, ..., N
$$
 (2)

As mentioned in the text we consider 8 outcomes which are absorbing states. 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. Since the "Did Statins Reduce the Health and Health Care Costs of Obesity?" article uses cohort simulations, this table presents descriptive statistics for the 2010 cohort used as baseline. 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) in Table 9. A number of them are statistically significant, and so we perform a robustness check on simulations not including these restrictions in section 7.2.

We have three other three other types of outcomes.

 \overline{a}

First, we have binary outcomes which are not an absorbing state. 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.

Second, we have ordered outcomes. These outcomes are also modeled as in (1) recognizing the observation rule is a function of unknown thresholds V_m . Similarly to binary outcomes, we allow for state-dependence by including the lagged outcome on the right-hand side.

¹⁰ With some abuse of notation, $j_i - 1$ denotes the previous age at which the respondent was observed.

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 term $e_{i,j,m}$ is a time-varying shock specific to age j_i . We assume that this last shock is normally distributed and uncorrelated across diseases. Unobserved difference h_{im} are persistent over time and are allowed to be correlated across diseases $m = 1, ..., M$. We assume that these have a normal distribution with covariance matrix W_{n} .

The parameters $q_1 = (\{b_m, g_m, V_m\}_{m=1}^M, \text{vech}(W_h))$ $q_1 = (\{b_m, g_m, V_m\}_{m=1}^M, \text{vech}(W_n))$, can be estimated by maximum simulated 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 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 h_i 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)

$$
l_{i}^{-0}(q;h_{i},h_{i,j_{i0}}) = \hat{e}_{i}^{(M-1)} \bigoplus_{\hat{\theta} \atop \hat{\theta}^{m=1}}^{j_{\hat{\theta}^{i}}}\sum_{j=j_{i1}}^{j_{\hat{\theta}^{i}}} P_{ij,m}(q;h_{i})^{(1-h_{ij-1,m})(1-h_{ij,M})} \bigoplus_{\hat{\theta}^{i}}^{i} \hat{e}_{i}^{(j)} \bigoplus_{j=j_{i1}}^{j_{\hat{\theta}^{i}}} P_{ij,M}(q;h_{i}) \bigoplus_{\hat{\theta}^{i}}^{i} (3)
$$

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

To obtain the likelihood of the parameters given the observables, it remains to integrate out unobserved heterogeneity. The complication is that $h_{i,j_{i0},-m}$, the initial outcomes in each hazard is 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 $p(h_i | h_{i,j_0})$ (Wooldridge, 2000). Implementing this solution amounts to including initial outcomes at baseline each hazard. This is equivalent to writing

$$
\eta_i = \Gamma h_{i0} + \alpha_i
$$

$$
\alpha_i \sim N(0, \Omega_\alpha)
$$

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

$$
l_i(q; h_{i,j_{i0}}) = \partial_l l_i(q; a_i, h_{i,j_{i0}}) dF(a_i)
$$
\n
$$
(4)
$$

To estimate the model, we make use of maximum simulated likelihood. We replace (4) with a simulated counterpart based on R draws from the distribution of σ . We them optimize over this simulated likelihood using the BFGS algorithm. We could not obtain convergence of the joint estimator. So we assumed the distribution of a_i to be degenerate. This yielded the simpler estimation problem where each equation can be estimated separately.

One problem fitting the wealth and earnings distribution is that they have a long left-tail and wealth has some negative values. We use a generalization of the inverse hyperbolic sine transform (IHT), presented in (MacKinnon & Magee, 1990). First denote the variable of interest y . The hyperbolic sine transform is

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

The inverse of the hyperbolic sin transform is

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

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

$$
r(y) = h(qy)/q \tag{7}
$$

Such that we can specify the regression model as

$$
r(y) = xb + e, e \sim N(0, s^2). \tag{8}
$$

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

$$
g(y) = \frac{h(q(y + w)) - h(qw)}{qh'(qw)}
$$
\n(9)

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

We specify (8) in terms of the transformation g. The shape parameters can be estimated from the concentrated likelihood for q, w . We can then retrieve b, s by standard OLS.

Upon estimation, we can simulate

$$
\tilde{g} = x\hat{b} + S\tilde{b}
$$
 (10)

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

$$
h(q(y + w)) = qh'(qw)\tilde{g} + h(qw)
$$

$$
\tilde{y} = \frac{\sinh[qh'(qw)\tilde{g} + h(qw)] - qw}{q}
$$

Tables 10-14 give parameter estimates for the transition models.

5.2 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 15 presents the results. Some differences exist but in general the fit is satisfactory.

5.3 Quality Adjusted Life Years

As an alternative measure of life expectancy, we compute a quality adjusted life year 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 UK sample. Later a scoring system based on a US sample was generated (Shaw JW et al, 2005). Since the HRS does not ask the appropriate questions for compute EQ-5D, but the MEPS does, we use 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 Table 26. If a person is living in a nursing home, then an additional 0.10 is subtracted from the computed QALY.

6 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.

6.1 Information Available and Empirical Strategy

For the transition model, we need to first to obtain outcomes listed in Table 16. Ideally, we need information on

$$
f_t(y_{i1},...,y_{iM}) = f_t(y_i)
$$
\n(11)

where *t* denotes calendar time, and $y_i = (y_{i1},..., y_{iM})$ 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

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

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, $f_{t_0}(y_i)$.

We make the assumption that only some part of $f_i(y_i)$ 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.

6.2 Model and Estimation

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

$$
y_i^* = m + e_i \tag{13}
$$

where e_i is normally distributed with mean zero and covariance matrix W. It will be useful to write the model as

$$
y_i^* = m + L_w / \eta_i \tag{14}
$$

where L_w is a lower triangular matrix such that $L_w L_w' = W$ and $h_i = (h_{i1},...,h_{iM})'$ are standard normal. We observe $y_i = G(y_i^*)$ 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.

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

$$
q_{MSL} = \arg \max_{q = (m, W)} \frac{1}{N} \sum_{i=1}^{N} \log \frac{1}{R} \sum_{r=1}^{R} \tilde{Pr}(y_i | q)_r
$$
 (15)

where $\frac{1}{R}$ $\Pr^R[\Pr(y_i | q)]$ $\frac{1}{R} \hat{\sigma}^R_{r=1} \tilde{Pr}(y_i | q)$, is a consistent estimate of $\tilde{Pr}(y_i | q)$. 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 *m* 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

$$
m_i = z_i b \tag{16}
$$

and the whole analysis is done conditional on z_i .

For binary and ordered outcomes, we fix $W_{m,m}$ =1 which fixes the scale. Also we fix the location of the ordered models by fixing thresholds as $t_0 = -4$, $t_1 = 0$, $t_k = +4$ where K denotes the number of categories for a particular outcome. Because some of the binary outcomes are rare, we fix correlations to zero between two outcomes if both fraction positive are below 10%. Furthermore, we fix to zero the correlation between selected outcomes (say earnings) and their selection indicator. Hence, we consider two-part models for these outcomes.

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

We start with the first outcome y_{ij}^* y_{i1}^* , a discrete outcome.

1. A draw of $heta_{i1}$ consistent with observed choice y_{i1} is $1^{-m_{i1}}$ \setminus $1 \quad \tilde{u}$ \setminus \sqsubseteq $1^{-m_{i1}}$ $,11$, $,11$, $,11$ 1 $\tilde{u}_1 = \mathsf{F}^{-1}[\tilde{u}_{i1}\mathsf{F}(\frac{\bar{c}_{i1}-m_{i1}}{L_{i0(1)}}) + (1-\tilde{u}_{i1})\mathsf{F}(\frac{c_{i1}-m_{i1}}{L_{i0(1)}})]$ $heta_{i1} = \mathsf{F}^{-1}[\tilde{u}_{i1} \mathsf{F}(\frac{c_{i1} - m_{i1}}{L_{W,11}}) + (1 - \tilde{u}_{i1}) \mathsf{F}(\frac{c_{i1} - m_{i1}}{L_{W,11}})]$ $= F^{-1} [\tilde{u}_{i1} F(\frac{\bar{c}_{i1} - m_{i1}}{L_{i1}}) + (1 - \tilde{u}_{i1}) F(\frac{c_{i1} - c_{i1}}{L_{i1}})]$ (17)

where $\overline{c}_{i1} = \begin{cases} 1 + \mathbf{n} y_{i1} - \mathbf{n} \\ 0 & \text{if } i \end{cases}$, $\mathcal{L}_{i1} = \begin{cases} 0 & \mathbf{n} y_{i1} \\ 0 & \text{if } i \end{cases}$ $1 - 10$ ϵ Ω 241 $1 - 0$ $1 - 1$ 1 y_{i1} if $y_{i1} = 1$ i 0 if $y_{i1} = 1$, 0 if $y_{i1} = 0$ ⁷⁻⁴¹ $\frac{1}{1}$ - \times if $y_{i1} = 0$ $i1 - 1$ $i \in \mathcal{I}$ $i \in \mathcal{I}$ $i \in \mathcal{I}$ iI^{-1} α $i\epsilon$ β γ $\frac{\epsilon}{4}$ $i1 - 0$ $1 - 1$ j $y_{i1} = 1$ *i* 0 if y $\overline{c}_{i1} = \begin{cases} 0 & \text{if } i \neq j \\ 0 & \text{if } j \neq k \end{cases}$ $y_{i1} = 0$ ² $i = 1$ **j** $-$ + **if** y $i \neq \text{if } y_{i1} = 1$ $i \neq 0$ if $y_{i1} =$ $=\frac{1}{1} \left(\frac{1}{2} \frac{1}{2}$ $\int_{1}^{1} 0$ if $y_{i1} = 0$ ² if $y_{i1} =$ 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

$$
\overline{c}_{i1} = t_k, \overline{c}_{i1} = t_{k-1} \text{ if } y_{i1} = k
$$

where t_k are parameters to be estimated.

- 2. The probability of that first outcome is $Pr(y_{i} | q) = F(\frac{c_{i1} m_i}{l_{i1}}) F(\frac{c_{i1}}{l_{i1}})$ $\tilde{\Pr}(y_{i1} | q) = \frac{\sum_{i=1}^{n} c_i - m_i}{L_{w,i1}} - \frac{\sum_{i=1}^{n} c_i - m_i}{L_{w,i1}})$ $y_{i1} | q$) = $F(\frac{c_{i1} - m_i}{L_{w,i1}}) - F(\frac{c_{i1} - m_i}{L_{w,i1}})$ $=$ $\frac{\overline{c}_{i1} - m_i}{I}$ $\frac{\overline{c}_{i1} - m_i}{I}$
- 3. Now a draw of h_{i2} consistent with y_{i2} and the draw \tilde{h}_{i1} is given by 2^{- m_{i}}2^{- $L_{W,21}$ n_{i1} , (1 \tilde{n}) \Box ($\frac{q_2 - m_{i2} - L_{W,21} n_{i1}}{n}$} 1 $\tilde{u}_1 = \sum_{i=1}^{n} \left[\tilde{u}_{i2} \mathcal{F}(\frac{\bar{c}_{i2} - m_{i2} - L_{W,21}h_{i1}}{L_{W,22}}) + (1 - \tilde{u}_{i2}) \mathcal{F}(\frac{c_{i2} - m_{i2} - L_{W,21}h_{i1}}{L_{W,22}}) \right]$ $\widetilde{h}_{i2} = \mathsf{F}^{-1}[\widetilde{u}_{i2}\mathsf{F}(\frac{\bar{c}_{i2}-m_{i2}-L_{W,21}h_{i1}}{L_{W,22}}) + (1-\widetilde{u}_{i2})\mathsf{F}(\frac{c_{i2}-m_{i2}-L_{W,21}h_{i2}}{L_{W,22}})]$ $= F^{-1}[\tilde{u}_{i2}F(\frac{\bar{c}_{i2}-m_{i2}-L_{W,21}h_{i1}}{L_{W,21}}) + (1-\tilde{u}_{i2})F(\frac{c_{i2}-m_{i2}-L_{W,2}}{L_{W,21}})]$
- $,22$, $\begin{array}{ccc} 12 & 12 \end{array}$, $\begin{array}{ccc} 12 & 12 \end{array}$, $\begin{array}{ccc} 22 & 12 \end{array}$ $W,22$ and U_1 is the set of L_1 4. Then the probability is given by 2 2 ,21 1 2 2 ,21 2 $\widetilde{\Pr}(\mathcal{Y}_{i1}, \mathcal{Y}_{i2} | q) = \widetilde{\Pr}(\mathcal{Y}_{i1} | q) [\mathsf{F}(\frac{\overline{c}_{i2} - m_{i2} - L_{W,21} \bar{r}_{i1}}{L_{W,22}}) - \mathsf{F}(\frac{c_{i2} - m_{i2} - L_{W,21} \bar{r}_{i2}}{L_{W,22}})]$ $y_{i1}, y_{i2} | q$) = $\widetilde{\Pr}(y_{i1} | q) [\overline{\Gamma(\frac{\overline{c}_{i2} - m_{i2} - L_{W,21} \bar{r}_{i1}}{L_{W,22}})} - \overline{\Gamma(\frac{c_{i2} - m_{i2} - L_{W,21} \bar{r}_{i1}}{L_{W,22}})}]$ W, 22 L_{W} $= \widetilde{\Pr}(y_{i1} | q) [\overline{\mathsf{F}}(\frac{\overline{c}_{i2} - m_{i2} - L_{W,21} \overline{r}_{i1}}{L}) - \overline{\mathsf{F}}(\frac{c_{i2} - m_{i2} - m_{i3} - \overline{r}_{i1}}{L})]$ (18)
- 5. Cycle trough 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

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

- 7. The probability is $_{1,m_0}$ - m_{i,m_0} - $\sum_{s=1}^{m_0-1} L_{\text{W},m_0}$ $\widetilde{\text{Pr}}(\mathcal{Y}_{i,m_0} \mid q) = \frac{1}{L_{\mathcal{W},m_0,m_0}} \mathcal{F}(\frac{\mathcal{Y}_{i,m_0} - m_{i,m_0} - \sum_{s=1}^{m_0-1} L_{\mathcal{W},m_0,s} \tilde{\mathcal{P}}_{is}}{L_{\mathcal{W},m_0,m_0}})$ m_0, m_0 *L*_W, m_0, m_1 y_{i,m_0} – m_{i,m_0} – $\sum_{i=1}^{m_0} L_i$ $\mathcal{Y}_{i,m_0}\mid q) = \frac{1}{L_{\mathcal{W},m_0,m_0}} \mathcal{F}(\frac{\mathcal{Y}_{i,m_0}-m_{i,m_0}-\sum_{s=1}^{m_0}-L_{\mathcal{W},m_0,s}n_{i,s_0})}{L_{\mathcal{W},m_0,m_0}}$ $\int_{-1}^{10^{-1}} L_{\text{W}}$ W, m_0, m_0 L_W $=\frac{1}{I_{\text{max}}} \mathcal{F}(\frac{y_{i,m_0}-m_{i,m_0}-\sum_{I_{\text{max}}}}{I_{\text{max}}}$
- 8. Hence $\Pr(y_{i_1},..., y_{i,m_0} | q) = \Pr(y_{i_1},..., y_{i,m_0-1} | q) \Pr(y_{i,m_0} | q)$
- 9. Cycle trough 6 to 8 until reach $m_1 1$, 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} can be observed. A draw consistent with $y_{i,m}$ is given by

$$
\tilde{\mathcal{h}}_{_{im_{_{1}}}} = \mathsf{F}^{\mathsf{-1}}[\tilde{u}_{_{im_{_{1}}}}] \text{ if } \mathcal{Y}_{ij} = 0
$$

and

$$
\tilde{\boldsymbol{h}}_{im_1} = \frac{y_{i,m1} - m_{i,m1} - \sum_{s=1}^{m_1-1} L_{W,m_1,s} \tilde{\boldsymbol{h}}_{is}}{L_{W,m_1,m_1}} \text{ if } \mathbf{y}_{ij} = 1
$$

- If y_{i} is continuous and given by a draw similar to (7) if a binary outcome.
- 11. The probability is then

$$
\tilde{\Pr}(y_{i,m_i} | q) = \left[\frac{1}{L_{W,m_i,m_1}} \mathcal{F}(\frac{y_{i,m_1} - m_{i,m_1} - \sum_{s=1}^{m_1-1} L_{W,m_1,s} \tilde{h}_{is}}{L_{W,m_1,m_1}}) \right]^{I(y_{i,j}=1)}
$$

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

- 12. Cycle 10-11 until reach *M*.
- 13. Repeat 1-9 R times and calculate $\frac{1}{R}$ $\Pr^R[\Pr(y_i | q)]$ $\frac{1}{R}\mathring{\bigtriangleup}^R_{r=1} \tilde{\Pr}(y_i \mid q)$ _r.
- 14. Repeat for each *i* = 1,...,*N*

We use draws from Halton sequences to generate uniform random draws (Train, 2003). Note that draws {{{ , } 1,..., }1,..., }1,..., *im ^r ^m ^M ^r ^R ⁱ ^N u* = = = are kept fixed trough estimation. For the first past, we used 10 draws along each dimension.

Because some parameters are naturally bounded, we re-parameterize the problem to guarantee an interior solution. In particular, we parameterize

$$
W_{m,m} = \exp(d_m), \ m = m_0 - 1, ..., M
$$

$$
W_{m,n} = \tanh(\chi_{m,n}) \sqrt{W_{m,m} W_{n,n}}, \ m, n = 1, ..., M
$$

$$
t_{m,k} = \exp(g_{m,k}) + t_{k-1}, \ k = 2, ..., K_m - 1, m \text{ ordered}
$$

and estimate the $(d_{m,m}, X_{m,n}, g_k)$ instead of the original parameters. Table 17 gives parameter estimates for the indices while Table 18 gives parameter estimates of the covariance matrix in the outcomes.

The latent model is written as

$$
y_i^* = m + L_w / N_i
$$

Each marginal has a mean change equal to $E(y | m) = (1 + t)g(m)$, where t 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 m^* where $m^* = g^{-1}(E(y | m)/(1 + t))$. We use these new intercepts to simulate new outcomes.

7 Government Revenue 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:

7.1 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 spouse's 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 spouse's 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.

7.2 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.

7.3 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. Table 11 contains the estimates for this model.

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.

7.4 Medical Costs Estimation

 \overline{a}

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 spending¹¹, 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 2002-2004 Medical Expenditure Panel Survey ($n = 14,098$) for these regressions for persons not Medicare eligible, and the 2002-2004 Medicare Current Beneficiary Survey ($n = 33, 231$) for spending for those that are eligible for Medicare. Those eligible for Medicare include people eligible due to age (65+) or due to disability status. A comparison across these different sources is provided in Table 2.

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. Table 19 shows the model estimation results for total, Medicaid, and out of pocket spending, while Table 20 shows the model estimation results for the Medicare spending. These estimation results only use the MCBS dataset.

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

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 1999-2004 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 Table 21. 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, Dowd, and Feldman, 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, we applied adjustment factors to the predicted three types of individual medical spending so that in year 2004, the predicted per-capita spending in FEM equal the corresponding spending in National Health Expenditure Accounts (NHEA), for age group 55-64 and 65 and over, respectively. Table 22 shows how these adjustment factors were determined by using the ratio of expenditures in the NHEA to expenditures predicted in the FEM.

The Medicare Current Beneficiaries Survey (MCBS) 2006 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 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.

Since only one year of Part D enrollment is available in the MCBS, only a cross sectional model of Part D enrollment is estimated, rather than a transition model as with Part B enrollment. A probit model is estimated to link demographics, economic status, current health, and functional status to Part D enrollment - see Tables 23 and 24 for estimates. 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.

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.

7.5 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 (\$3100) 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.

8 Implementation of the FEM

The FEM is implemented in multiple parts. Estimation of the transition and cross sectional models is performed in Stata, the incoming cohort model is estimated in Ox, and 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.

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.

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Technical Tables

List of Technical Tables

Prevalence in 1978 is based on NHANES II 1976-1980; Prevalence in 2004 is based on NHANES 2001-2006 pooled data. BMI is calculated using self-reported weight and height

Control variable Mean Standard Deviation Minimum Maximum age 51.96 0.548 51 52.92 blackk and 0.159 0.366 0 1 hispanic 0.147 0.355 0 1 less than high school 0.123 0.329 0 1 0.596 0.491 0 1 malee and 0.465 0.499 0 1 $\mathbf{1}$ ever smoked (includes current) 0.549 0.498 0 1 widowed at baseline 0.0222 0.147 0 single at baseline 0.298 0.457 0 1 log AIME/10 at baseline 0.7 0.141 0.288 1.132 log quarters/10 at baseline 0.678 0.426 0.0927 0.151 0.678 Any DB at baseline 0.23 0.421 0 1 NRA 57-61 0.0575 0.233 0 1 $\mathbf{1}$ NRA 62-63 0.0363 0.187 0 1 NRA 64+ $^{+}$ 0.0949 0.293 0 1 Any DC at baseline 0.293 0.455 0 1
(IHT of DC wealth in 1000s)/100 if any DC, zero else 0.0111 0.0194 0 0.0996 (IHT of DC wealth in $1000s/100$ if any DC, zero else 0.0111 0.0194 0 Unweighted Statistics

Notes: x denotes a parameter which is allowed to be estimated. Other controls include initial conditions, demographics, db and dc plan characteristics, AIME and social security quarters of coverage. Tests do not include nursing home restriction or claimed DI

t statistics in parentheses

t statistics in parentheses

t statistics in parentheses

 (4.98)

t statistics in parentheses

Household Wealth if nonzero Individual earnings if working

t statistics in parentheses

