Technical Documentation: The Health Economic Medical Innovation Simulation - PSID Version

Precision Health Economics

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Acronyms

ACA Affordable Care Act

ACS American Community Survey

ADL Activities of Daily Living

BMI Body Mass Index

CBO Congressional Budget Office

CMS Centers for Medicare & Medicaid Services

CPI Consumer Price Index

EQ-5D EuroQol Five Dimensions Questionnaire

FAM Future Adult Model

FEM Future Elderly Model

GDP Gross Domestic Product

HC Household Component

HRQoL Health-Related Quality of Life

HRS Health and Retirement Study

IADL Instrumental Activities of Daily Living

MCBS Medicare Current Beneficiary Survey

MEPS Medical Expenditure Panel Survey

MINT Modeling Income in the Near Term

NHIS National Health Interview Survey

OASI Old-Age and Survivors Insurance

OLS Ordinal Least Squares

OOP Out-of-Pocket

PHE Precision Health Economics

PSID Panel Study of Income Dynamics

QALY Quality-Adjusted Life Year

SF-12 12-Item Short Form Health Survey

THEMIS The Health Economics Medical Innovation Simulation

UK United Kingdom

US United States

USC University of Southern California

1 Functioning of the dynamic model

1.1 Background

The Health Economics Medical Innovation Simulation (THEMIS) is a microsimulation model originally developed out of an effort to examine health and health care costs among the elderly Medicare population (age 65+). It is based on the foundation of the Future Elderly Model (FEM) and Future Adult Model (FAM). A description of the original incarnation of the model can be found in Goldman et al. (2004). The original work was funded by the Centers for Medicare & Medicaid Services (CMS) and carried out by a team of esteemed academic and RAND Corporation researchers, including Precision Health Economics (PHE) founders Dana P. Goldman and Darius N. Lakdawalla.

1.2 Overview

The defining characteristic of the model is the modeling of real rather than synthetic cohorts, all of whom are followed at the individual level. This allows for more heterogeneity in behavior than would be allowed by a cell-based approach. In addition, since the Panel Study of Income Dynamics (PSID) interviews both respondent and spouse, it is possible to link records in order to calculate household-level outcomes, which depend on the responses of both spouses.

The model has three core components:

- The replenishing cohort module predicts the economic and health outcomes of new cohorts of 25/26 year-olds. This module takes in data from the PSID 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 25+ population in any given year.
- The transition module calculates the probabilities of transitioning across various health states and financial outcomes. The module incorporates input 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 PSID.
- The policy outcomes module aggregates projections of individual-level outcomes into policy outcomes such as taxes, medical care costs, and disability benefits. This component takes into account public and private program rules to the extent allowed by the available outcomes.

Figure 1 provides a schematic overview of the model. In this example, we start in 2014 with an initial population ages 25+ taken from the PSID. We then predict outcomes using our estimated transition probabilities (see section 3.1). 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 replenishing cohort of 25/26 year-olds enters (see section 4). This entrance forms the new age 25+ population, who then proceeds through the transition model as before. This process is repeated until we reach the final year of the simulation.

1.3 Comparison with other microsimulation models of health expenditures

The precursor to THEMIS, the FEM, was unique among models that make health expenditure projections. It was the only model that projected health trends rather than health expenditures.

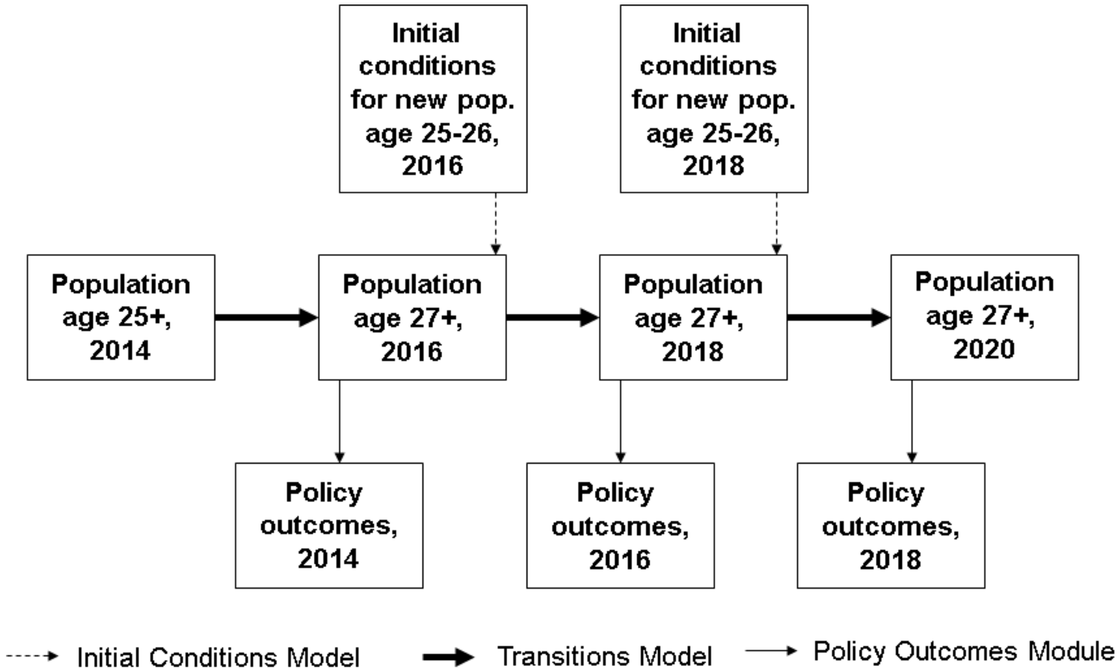

Figure 1: Architecture

It was also unique in generating mortality projections based on assumptions about health trends rather than historical time series. Incorporating the PSID extended the FEM to younger ages, adding additional dimensions to the simulation. Events over the life course, such as marital status and childbearing are simulated. Labor force participation is modeled in greater detail, distinguishing between out-of-labor force, unemployed, working part-time, and working full-time.

1.3.1 Congressional Budget Office Long-Term Model

The Congressional Budget Office (CBO) uses time-series techniques to project health expenditure growth in the short term and then makes an assumption on long-term growth (The Congressional Budget Office, 2009). They use a long term growth of excess costs of 2.3 percentage points starting in 2020 for Medicare. They then assume a reduction in excess cost growth in Medicare of 1.5% through 2083, leaving a rate of 0.9% in 2083. For non-Medicare spending they assume an annual decline of 4.5%, leading to an excess growth rate in 2083 of 0.1%.

1.3.2 Centers for Medicare and Medicaid Services

The Centers for Medicare & Medicaid Services (CMS) perform 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 (e.g. if nominal Gross Domestic Product (GDP) growth is 4%, health care expenditure growth will be 5%).

1.3.3 Modeling Income in the Near Term Model

The Modeling Income in the Near Term (MINT) is a microsimulation model developed by the Urban Institute and others for the Social Security Administration to enable policy analysis of proposed changes to Social Security benefits and payroll taxes (Smith and Favreault, 2013). MINT uses the Survey of Income and Program Participation as the base data and simulates a range of outcomes, with a focus on those that will impact Social Security. Recent extensions have included health insurance coverage and Out-of-Pocket (OOP) medical expenditures. Health enters MINT via self-reported health status and self-reported work limitations. MINT simulates marital status and fertility.

2 Data sources used for estimation

The PSID is the main data source for the model. We estimate models for assigning characteristics for the replacement cohorts in the Replenishing Conditions Module. These are summarized in Table 1. We estimate transition models for the entire PSID population in the Transition Model Module. Transitioned outcomes are described in Table 2.

2.1 Panel Survey of Income Dynamics

The PSID waves 1999-2013 are used to estimate the transition models. The PSID interviews occur every two years. We create a dataset of respondents who have formed their own households, either as single heads of households, cohabitating partners, or married partners. These heads, wives, and "wives" (males are automatically assigned head of household status by the PSID if they are in a couple) respond to the richest set of PSID questions, including the health questions that are critical for our purposes. We use all respondents ages 25+. When appropriately weighted, the PSID is representative of households in the United States (US). We also use the PSID as the host data for full population simulations that begin in 2009. Respondents ages 25/26 are used as the basis for the synthetic cohorts that we generate, used for replenishing the sample in population simulations or as the basis of cohort scenarios.

The PSID continually adds new cohorts that are descendants (or new partners/spouses of descendants). Consequently, updating the simulation to include more recent data is straightforward.

2.2 Health and Retirement Study

The Health and Retirement Study (HRS) waves 1998-2012 are pooled with the PSID for estimation of mortality and widowhood models. The HRS has a similar structure to the PSID, with interviews occurring every two years. The HRS data is harmonized to the PSID for all relevant variables. We use the dataset created by RAND (RAND HRS, version P) as our basis for the analysis. We use all cohorts in the analysis. When appropriately weighted, the HRS in 2010 is representative of US households where at least one member is at least age 51. Compared to the PSID, the HRS includes more older Hispanics and interviews more respondents once they have entered nursing homes.

2.3 National Health Interview Survey

The National Health Interview Survey (NHIS) contains individual-level data on height, weight, smoking status, self-reported chronic conditions, income, education, and demographic variables. It is a repeated cross-section done every year for several decades. But the survey design has been significantly modified several times. Before year 1997, different subgroups of individuals were asked about different sets of chronic conditions, after year 1997, a selected sub-sample of the adults were asked a complete set of chronic conditions. THEMIS uses the 1997-2010 NHIS data for projecting the trends in health and risk factors for future 25/26 year-olds. A review of survey questions is provided in Table 4. 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.

2.4 American Community Survey

The American Community Survey (ACS) is an ongoing survey by the US Census Bureau. The survey gathers information on social and economic outcomes, housing, and demographics. Each year around 3.5 million households are surveyed. THEMIS uses the ACS data to project the trends in social outcomes for future 25/26 year-olds.

2.5 Medical Expenditure Panel Survey

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 US. 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 HC collects data from a representative sub sample of households drawn from the previous year's NHIS. Since the NHIS does not include the institutionalized population, neither does the MEPS: this implies that we can only use the MEPS to estimate medical costs for the non-elderly (ages 25-64) 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 ages 25-64 is about 15,800 in each year. The MEPS has comparable measures of social-economic variables as those in the PSID, including age, race/ethnicity, educational level, census region, and marital status. We estimate expenditures and utilization using 2007-2010 data. See Section 5.1 for a description. THEMIS also uses the MEPS 2001-2003 data for Quality-Adjusted Life Year (QALY) model estimation.

2.6 Medicare Current Beneficiary Survey

The Medicare Current Beneficiary Survey (MCBS) is a nationally representative sample of aged, disabled and institutionalized Medicare beneficiaries. The MCBS attempts to interview each respondent twelve times over three years, regardless of whether he or she resides in the community, a facility, or transitions between community and facility settings. The disabled (under 65 years of age) and oldest-old (age 85+) 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. The MCBS years 2007-2010 are used for estimating medical cost and enrollment models. See section 5.1 for discussion.

3 Estimation

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

3.1 Transition model

We consider a large set of outcomes for which we model transitions. Table 5 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 25+ population, each respondent goes through an individual-specific series of intervals. Hence, we have an unbalanced panel over the age range starting from 25 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 $j_i = j_{i0}, \ldots, j_{iT_i}$.

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

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

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

The term $\varepsilon_{i,j_i,m}$ is a time-varying shock specific to age j_i. We assume that this last shock is normally distributed and uncorrelated across diseases. We approximate a_{m,j_i} with an age spline with knots at ages 35, 45, 55, 65, and 75. This simplification is made for computational reasons since the joint estimation with unrestricted age fixed effects for each condition would imply a large number of parameters. The absorbing outcome, conditional on being at risk, is defined as

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

The occurrence of mortality censors observation of other outcomes in a current year.

A number of restrictions are placed on the way feedback is allowed in the model. Table 6 documents restrictions placed on the transition model. We also include a set of other controls. A list of such controls is given in Table 7 along with descriptive statistics.

We have five other types of outcomes:

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

1. First, we have binary outcomes which are not an absorbing state, such as starting smoking. We specify latent indices as in (1) for these outcomes as well, but where the lag dependent outcome also appears as a right-hand side variable. This allows for state-dependence.

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

3. The third type of outcomes we consider are censored outcomes, such as financial wealth. For wealth, there are a non-negligible number of observations with zero and negative wealth. For these outcomes with non-negligible numbers of zeros, we use a two-part approach where the first part is a model that predicts whether or not the final outcome is zero as in (1), and the second part predicts the outcome conditional on it not being zero. In total, we have M outcomes.

4. The fourth type of outcomes are continuous outcomes modeled with ordinary least squares. For example, we model transitions in Body Mass Index (BMI) using log(BMI). We allow for state-dependence by including the lagged outcome on the right-hand side.

5. The final type of models are categorical, but without an ordering. For example, an individual can transition to being out of the labor force, unemployed, or working (either full- or part-time). In situations like this, we utilize a multinomial logit model, including the lagged outcome on the right-hand side.

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

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

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

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

3.1.1 Further details on specific transition models

This section describes the modeling strategy for particular outcomes.

Employment status Ultimately, we wish to simulate if an individual is out of the labor force, unemployed, working part-time, or working full-time at time t. We treat the estimation of this as a two-stage process. In the first stage, we predict if the individual is out of the labor force, unemployed, or working for pay using a multinomial logit model. Then, conditional on working for pay, we estimate if the individual is working part- or full-time using a probit model.

Earnings We estimate last calendar year earnings models based on the current employment status, controlling for the prior employment status. Of particular concern are individuals with no earnings, representing approximately twenty-five percent of the unemployed and seventy-eight percent of those out of the labor force. This group is less than 0.5% of the full- and part-time populations. We use a two-stage process for those out of the labor force and unemployed. The first stage is a probit that estimates if the individual has any earnings. The second stage is an Ordinal Least Squares (OLS) model of log(earnings) for those with non-zero earnings. For those working full- or part-time, we estimate OLS models of log(earnings).

Relationship status We are interested in three relationship statuses: single, cohabitating, and married. In each case, we treat the transition from time t to time $t+1$ as a two-stage process. In the first stage, we estimate if the individual will remain in their current status. In the second stage, we estimate which of the two other states the individual will transition to, conditional on leaving their current state.

Childbearing We estimate the number of children born in two-years separately for women and men. We model this using an ordered probit with three categories: no new births, one birth, and two births. Based on the PSID data, we found the exclusion of three or more births in a two-year period to be appropriate.

3.1.2 Inverse hyperbolic sine transformation

One problem fitting the wealth distribution is that it has a long right tail and some negative values. 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

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

The inverse of the hyperbolic sine transform is

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

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

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

Such that we can specify the regression model as

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

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

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

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

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

Upon estimation, we can simulate

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

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

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

The included estimates table (estimatesPSID.xml) gives parameter estimates for the transition models.

3.2 Quality-adjusted life years

As an alternative measure of life expectancy, we compute a QALY based on the EuroQol Five Dimensions Questionnaire (EQ-5D) instrument, a widely-used Health-Related Quality of Life (HRQoL) measure.[2] The scoring system for EQ-5D was first developed by Dolan (1997) using a sample from the United Kingdom (UK). Later, a scoring system based on a US sample was generated (Shaw et al., 2005). The PSID does not ask the appropriate questions for computing EQ-5D, but the MEPS does. We use a crosswalk from the MEPS to compute EQ-5D scores for PSID respondents.[3]

In order to predict HRQoL for the THEMIS simulation sample, we needed to build a bridge between PSID-based functional status and the EQ-5D score imputed into the PSID data. We used OLS regression to model the EQ-5D score predicted for the 1999–2013 PSID respondents as a function of chronic conditions, functional status, and self-reported health. The results are shown in Table 19. We uset the parameter estimates in Table 19 to predict the EQ-5D scores for the entire simulation sample. The resulting scores are representative of the US population.

4 Model for replenishing cohorts

We first discuss the empirical strategy, then present the model and estimation results. The model for replenishing cohorts integrates information coming from trends among younger cohorts with the joint distribution of outcomes in the current population of age 25 respondents in the PSID.

4.1 Model and estimation

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

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

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

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

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

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

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

[2] Section 7.1.1 gives some background on HRQoL measures.

[3] Section 7.1.2 describes EQ-5D in the MEPS. Details of the crosswalk model development are given in 7.1.3.

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

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

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

and estimate the $(\delta_m, \xi_{m,n}, \gamma_{m,k})$ instead of the original parameters. The parameter values are estimated using the *cmp* package in Stata (Roodman, 2011). Table 8 gives parameter estimates for the indices, while Table 9 gives parameter estimates of the covariance matrix in the outcomes.

4.2 Trends for replenishing cohorts

Using the jointly estimated models previously described, we then assign outcomes to the replenishing cohorts, imposing trends for some health, risk factor, and social outcomes. We currently impose trends on BMI, education, number of children, marital status, hypertension, and smoking status for these 25/26 year-olds. These trends are estimated using the NHIS (health and risk factors) or the ACS (social outcomes). All trends are halted after 2029. The trends are shown in Table 10, Table 11 and Table 12.

5 Government revenues and expenditures

This gives a limited overview of how revenues and expenditures of the government are computed.

5.1 Medical costs estimation

In THEMIS, 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. THEMIS models: total medical spending (medical spending from all payment sources), Medicare spending[4], Medicaid spending (medical spending paid by Medicaid), and OOP 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 (CPI). We use the 2007-2010 MEPS for these regressions for persons not Medicare eligible, and the 2007-2010 MCBS 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. Comparisons of prevalences and question wording across these different sources are provided in Tables 3 and 4, respectively.

In the baseline scenario, this spending estimate can be interpreted as the resources consumed by the individual given the manner in which medicine is practiced in the US during the post-part D era (2006-2010). Models are estimated for total, Medicaid, OOP spending, and Medicare spending.

[4]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 2007-2010 MCBS to model take up of Medicare Part B for both new enrollees into Medicare, as well as current enrollees without Part B. Estimates are based on weighted probit regression on various risk factors, demographic, and economic conditions. The PSID starting population for THEMIS does not contain information on Medicare enrollment. Therefore another model of Part B enrollment for all persons eligible for Medicare is estimated via a probit, and used in the first year of simulation to assign initial Part B enrollment status. Estimation results are shown in estimates table. The MCBS data overrepresents the portion enrolled in Part B, having a 97% enrollment rate in 2004 instead of the 93.5% rate given by Board of Trustees of the Federal Insurance and Federal Supplementary Insurance Funds (2006, Table III.A3). In addition to this baseline enrollment probit, we apply an elasticity to premiums of -0.10, based on the literature and simulation calibration for actual uptake through 2009 (Atherly et al., 2004; Buchmueller, 2006). The premiums are computed using average Part B costs from the previous time step and the means-testing thresholds established by the Affordable Care Act (ACA).

Since 2006, the MCBS contains data on Medicare Part D. The data gives the capitated Part D payment and enrollment. When compared to the summary data presented in the CMS 2007 Trustee Report, the 2006 per capita cost is comparable between the MCBS and the CMS Board of Trustees of the Federal Insurance and Federal Supplementary Insurance Funds (2007). However, the enrollment is underestimated in the MCBS, 53% compared to 64.6% according to the CMS. A cross-sectional probit model is estimated using the years 2007-2010 to link demographics, economic status, current health, and functional status to Part D enrollment - see the estimates table. To account for both the initial under reporting of Part D enrollment in the MCBS, as well as the CMS prediction that Part D enrollment will rise to 75% by 2012, the constant in the probit model is increased by 0.22 in 2006, to 0.56 in 2012 and beyond The per capita Part D cost in the MCBS matches well with the cost reported from the CMS. An OLS regression using demographic, current health, and functional status is estimated for Part D costs based on capitated payment amounts.

The Part D enrollment and cost models are implemented in the Medical Cost module. The Part D enrollment model is executed conditional on the person being eligible for Medicare, and the cost model is executed conditional on the enrollment model indicating enrollment for that year. Otherwise the person has zero Part D cost. The estimated Part D costs are added to Part A and B costs to obtain total Medicare cost, and any medical cost growth assumptions are then applied.

6 Implementation

THEMIS is implemented in multiple parts. Estimation of the transition and cross sectional models is performed in Stata. The replenishing cohort model is estimated in Stata using the *cmp* package (Roodman, 2011). The simulation is implemented in C++ for speed and flexibility and run in Linux. To match the two year structure of the PSID data used to estimate the transition models, THEMIS 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 THEMIS proceeds by first loading a population representative of the age 25+ US population in 2009, generated from the PSID. In two year increments, acTHEMIS 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 25/26 year-olds are added to the population. The number of new 25/26 year-olds added is consistent with estimates from the Census, stratified by race. Once the new states have been determined and new 25/26 year-olds added, the cross sectional models for medical costs are performed. Summary variables are then computed. Computation of medical costs includes the persons that died to account for end of life costs. To reduce 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.

THEMIS simulation incorporates input assumptions regarding the normal retirement age, real medical cost growth, and interest rates. The default assumptions are taken from the 2010 Social Security Intermediate scenario, adjusted for no price increases after the current year. When comparing a single healthcare system innovation (e.g. a new treatment) to the status quo, the future reduction in all-cause mortality and accompanying increases in medical expenditures are normally turned off. Different simulation scenarios are implemented by changing any of the following components: incoming cohort model, transition models, interventions that adjust the probabilities of specific transitions, and changes to assumptions on future economic conditions.

6.1 Intervention module

The intervention module can adjust characteristics of individuals when they are first read into the simulation "init interventions" or alter transitions within the simulation "interventions." At present, init interventions can act on chronic diseases, ADL or IADL limitations, program participation, and some demographic characteristics. Interventions within the simulation can currently act on mortality, chronic diseases, and some program participation variables. Interventions can take several forms. The most commonly used is an adjustment to a transition probability. One can also delay the assignment of a chronic condition or cure an existing chronic condition. Additional exibility comes from selecting who is eligible for the intervention. Some examples might help to make the interventions concrete:

- Example 1: Delay the enrollment into Social Security Old-Age and Survivors Insurance (OASI) by two years. In this scenario, claiming of Social Security benefits is transitioned as normal. However, if a person is predicted to claim their benefits, then that status is not immediately assigned, but is instead assigned two years later.

- Example 2: Cure hypertension for those with no other chronic diseases. In this scenario, any individual with hypertension (including those who have had hypertension for many years) is cured (hypertension status is set to 0), as long as they do not have other chronic diseases. This example uses the individuals chronic disease status as the eligibility criteria for the intervention.

- Example 3: Reduce the incidence of hypertension for half of men aged 55 to 65 by 10% in the first year of the simulation, gradually increasing the reduction to 20% after 10 years. This example begins to show the exibility in the intervention module. The eligibility criteria are more complex (half of men in a specific age range are eligible) and the intervention changes over time. Mathematically, the intervention works by acting on the incidence probability, ρ. In the first year of the simulation, the probability is replaced by $(1 - 0.5 * 0.1)\,\rho = 0.95\rho$. The binary outcome is then assigned based on this new probability. Thus, at the population level, there is a 5% reduction in incidence for men aged 55 to 65, as desired. After 10 years, the probability for this eligible population becomes $(1 - 0.5 * 0.2)\,\rho = 0.9\rho$.

More elaborate interventions can be programmed by the user.

7 Model development

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

7.1 Quality-adjusted life years

7.1.1 Health-related quality-of-life

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

7.1.2 Health-related quality-of-life in the Medical Expenditure Panel Survey

Because the health states measures in the PSID and THEMIS do not match the health states defined in any of the currently available HRQoL indexes, we used the MEPS to create a crosswalk file for HRQoL index calculation. The MEPS collects information on health care cost and utilization, demographics, functional status, and medical conditions. MEPS initiated a self-administered questionnaire for the 12-Item Short Form Health Survey (SF-12) instrument in the year 2000. It also included a self-administered questionnaire for the EQ-5D instrument in the years 2001 to 2003. We calculate the EQ-5D as the HRQoL measure in THEMIS.

The EQ-5D instrument includes five questions about the extent of problems in mobility, self-care, daily activities, pain, and anxiety/depression. The scoring system for the EQ-5D was first developed by Dolan (1997) using a UK sample. Later, a scoring system using a US sample was generated (Shaw et al., 2005). Based these 74,461 respondents in the MEPS 2001–2003, we calculate EQ-5D scores using the scoring algorithm (Shaw et al., 2005). The distribution of the EQ-5D index scores among these respondents is shown in Figure 2.

7.1.3 MEPS-PSID crosswalk development

The functional status measure in THEMIS is based on the PSID. It is a categorical variable including the following mutually exclusive categories: healthy, any IADL limitations (no ADL limitations), 1–2 ADL limitations, and 3 or more ADL limitations. The measures of ADL and IADL limitations in the PSID and MEPS are different. The PSID asks questions like "Do you have any problem in . . .", while the MEPS asks questions like "Does . . .help or supervision in . . .." We use the functional status measures comparable across the MEPS and the PSID (the host dataset), in order to compute the EQ-5D index scores using functional status in THEMIS. In the MEPS, an IADL limitation indicates receiving help or supervision using the telephone, paying bills, taking medications, preparing light meals, doing laundry, or going shopping. In the PSID, an IADL limitation indicates having difficulty in any IADL such as using the phone, managing money, or taking medications.

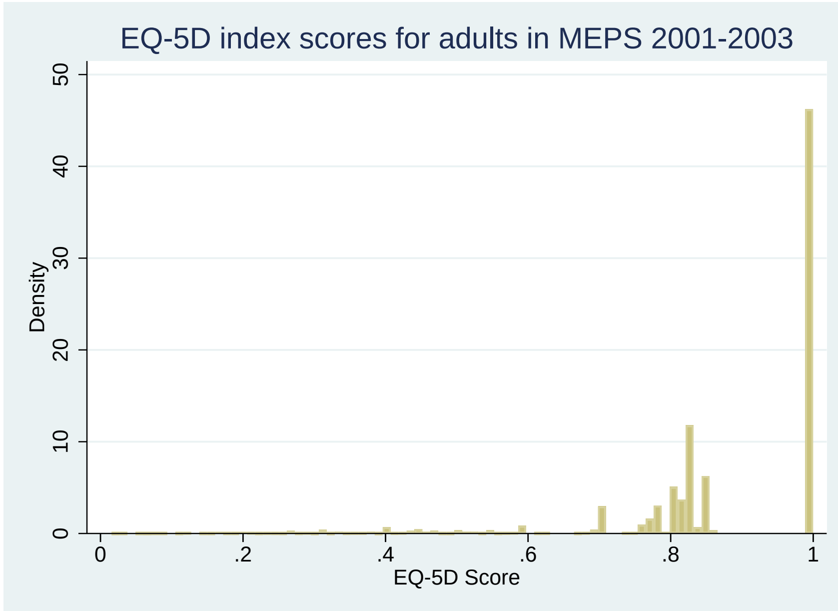

Figure 2: Distribution of the EQ-5D index scores for adults in the 2001–2003 MEPS

In addition to functional status limitations, we consider a measure of perceived health status available in both the PSID and the MEPS in the estimation of the EQ-5D index scores. Self-reported health is coded as 1-excellent to 5-poor in both surveys. As a part of the MEPS-PSID crosswalk, we calculate and use the relative value of the mean self-reported health in the PSID to that in the MEPS by age category.

Using the MEPS 2001–2003 data, we next use OLS regression to model the derived EQ-5D score as a function of seven chronic conditions – which are available in both the PSID and MEPS, IADL and ADL limitations, and an interaction term of the two measures of functional status. Three different models are considered. Estimation results are presented in Models I–III in Table 18. In addition, we show the estimation results by including variables representing self-reported health in the MEPS interacted with the age < 75 variable, and the mean value of self-reported health in the PSID relative to the MEPS interacted with the age ≥ 75 variable in Model IV of Table 18. Model V of Table 18 includes additional demographic variables. Model IV was used as the crosswalk described in Section 3.2 to calculate the EQ-5D scores in the PSID data for 1999–2013. Since Model IV and Model V are similar in model fit, we choose Model IV over Model V in order to estimate the EQ-5D scores according to an individuals' health status variables only.

8 Validation

We perform cross-validation and external corroboration exercises. Cross-validation is a test of the simulations internal validity that compares simulated outcomes to actual outcomes. External corroboration compares model forecasts to others forecasts.

8.1 Cross-validation

The cross-validation exercise randomly samples half of the PSID respondent IDs for use in estimating the transition models. The respondents not used for estimation, but who were present in the PSID sample in 1999, are then simulated from 1999 through 2013. Demographic, health, and economic outcomes are compared between the simulated (THEMIS) and actual (PSID) populations. Worth noting is how the composition of the population changes in this exercise. In 1999, the sample represents those 25 and older. Since we follow a fixed cohort, the age of the population will increase to 39 and older in 2013. This has consequences for some measures in later years where the eligible population shrinks. On the whole, the crossvalidation exercise is reassuring. There are differences that will be explored and improved upon in the future.

8.1.1 Mortality and demographics

Mortality and demographic measures are presented in Tables 13 and 14. Mortality incidence is comparable between the simulated and observed populations. Demographic characteristics do not differ between the two populations.

8.1.2 Health outcomes

Binary health outcomes are presented in Table 15. THEMIS underestimates the prevalence of ADL and IADL limitations compared to the crossvalidation sample. Binary outcomes, like cancer, diabetes, heart disease, and stroke do not differ. THEMIS underpredicts hypertension and lung disease compared to the crossvalidation sample.

8.1.3 Health risk factors

Risk factors are presented in Table 16. BMI is not statistically different between the two samples. Current smoking is not statistically different, but more individuals in the crossvalidation sample report being former smokers.

8.1.4 Economic outcomes

Binary economic outcomes are presented in Table 17. THEMIS underpredicts claiming of federal disability and overpredicts Social Security retirement claiming. Supplemental Security claiming is not statistically different between THEMIS and the crossvalidation sample. Working for pay is also not statistically different.

8.2 External corroboration

Finally, we compare THEMIS population forecasts to Census forecasts of the US population. Here, we focus on the full PSID population (ages 25+) and those ages 65+. For this exercise, we begin the simulation in 2009 and simulate the full population through 2049. Population projections are compared to the 2012 Census projections for years 2012 through 2049. See results in Table 20. By 2049, THEMIS forecasts for the population ages 25+ remain within 2% of Census forecasts.

9 Baseline Forecasts

In this section, we present baseline forecasts of THEMIS. The figures show data from the PSID for the 25+ population from 1999 through 2009 and forecasts from THEMIS for the 25+ population beginning in 2009.

9.1 Disease prevalence

Figure 3 depicts the chronic conditions we project for men, and Figure 4 depicts the historic and forecasted values for women. Figure 5 shows historic and forecasted levels for any ADL difficulties, three or more ADL difficulties, any IADL difficulties, and two or more IADL difficulties for men ages 25+. Figure 6 shows historic and forecasted levels for any ADL difficulties, three or more ADL difficulties, any IADL difficulties, and two or more IADL difficulties for women ages 25+.

10 Acknowledgments

Since the original FEM model was released, various extensions have been implemented by PHE as well as others. The work has also been extended to include economic outcomes such as earnings, labor force participation and pensions. Some of 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. THEMIS incorporates developments suported by the National Institutes of Aging and released by the University of Southern California (USC) Roybal Center for Health Policy Simulation (5P30AG024968-13, P30AG024968, and RC4AG039036).

This document describes the version of THEMIS using the PSID as the host dataset for the population.

The FEM and FAM have been developed by a large team over the last decade. The authors of the FAM technical specifications are Dana P. Goldman, Duncan Ermi Leaf, and Bryan Tysinger. Jay Bhattacharya, Eileen Crimmins, Christine Eibner, Étienne Gaudette, Geoff Joyce, Darius Lakdawalla, Pierre-Carl Michaud, and Julie Zissimopoulos have all provided expert guidance. Adam Gailey, Baoping Shang, and Igor Vaynman provided programming and analytic support during the first years of the FEM development at RAND. Jeff Sullivan then led the technical development for several years. More recently, the USC research programming team has supported model development, including the FAM development. These programmers include Patricia St. Clair, Laura Gascue, Henu Zhao, and Yuhui Zheng. Barbara Blaylock, Malgorzata Switek, and Wendy Cheng have greatly aided model development while working as research assistants at the USC.

11 Tables

Economic Outcomes	**Health Outcomes**	**Other Outcomes**
Work Status	BMI Category	Education
Earnings	Smoking Category	Partnered
Wealth	Hypertension	Partner Type
		Health Insurance

Table 1: Estimated outcomes in replenishing cohorts module

Economic Outcomes	**Health Outcomes**	**Marital Status**	**Other Outcomes**
Social Security Claiming	Mortality	Exit Single	Insurance Type
Disability Claiming	Heart Disease	Exit Cohabitation	
Non-zero Capital Income	Cancer	Exit Married	
Capital Income (if Non-zero)	Hypertension	Single to Married	
Non-zero Government Transfers	Diabetes	Cohabitation to Married	
Government Transfers (if Non-zero)	Lung Disease	Married to Cohabitation	
Non-zero Wealth	Start Smoking		
Wealth (if Non-zero)	Stop Smoking		
Labor Force Status (Out, Unemployed, Working)	ADL Status		
Employed Full- or Part-time (if Working)	IADL Status		
Any Earnings (if Unemployed)	Births/Paternity		
Any Earnings (if Not in Labor Force)	Self-reported Health		
Earnings (if Full-time)	BMI		
Earnings (if Part-time)	Partner Death		
Earnings (if Unemployed and any)			
Earnings (if Not in Labor Force and any)			

Table 2: Estimated outcomes in transitions module

					Prevalence %				
Source (years, ages)	Cancer	Heart Diseases	Stroke	Diabetes	Hypertension	Lung Disease	Depression	Overweight	Obese
HRS (2004-2008, 50-64)	8%	14%	4%	17%	45%	7%	26%	37%	42%
HRS (2004-2008, 65+)	20%	31%	11%	23%	64%	11%	20%	37%	33%
MCBS (2007-2010, 65+)	19%	41%	11%	25%	68%	17%	22%	38%	26%
MEPS (2007-2010, 25-49)	2%	6%	1%	4%	17%	4%	10%	35%	29%
MEPS (2007-2010, 50-64)	6%	16%	4%	14%	46%	7%	13%	37%	34%
MEPS (2007-2010, 65+)	14%	37%	13%	21%	68%	11%	11%	38%	26%
NHIS (2007-2009, 25-49)	2%	6%	1%	4%	16%	4%		34%	31%
NHIS (2007-2009, 50-64)	7%	14%	3%	13%	41%	7%		36%	35%
NHIS (2007-2009, 65+)	17%	32%	9%	19%	61%	10%		36%	27%
PSID (2007-2011, 25-49)	2%	5%	1%	4%	13%	3%	4%	37%	30%
PSID (2007-2011, 50-64)	7%	14%	3%	13%	35%	8%	4%	40%	34%
PSID (2007-2011, 65+)	16%	35%	9%	20%	55%	14%	2%	40%	28%

Table 3: Health condition prevalences in survey data

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

Table 4: Survey questions used to determine health conditions

			Type	At risk	Mean/fraction
Disease	heart disease		biennial incidence	undiagnosed	0.02
	hypertension		biennial incidence	undiagnosed	0.04
	stroke		biennial incidence	undiagnosed	0.01
	lung disease		biennial incidence	undiagnosed	0.01
	cancer		biennial incidence	undiagnosed	0.01
	diabetes		biennial incidence	undiagnosed	0.02
	depression		biennial incidence	undiagnosed	0.01
Risk Factors	Smoking Status	never smoked	ordered	all	0.50
		ex smoker	ordered	all	0.30
		current smoker	ordered	all	0.20
	Log BMI		continuous	all	3.33
	ADL Status	no ADLs	ordered	all	0.90
		1 ADL	ordered	all	0.04
		2 ADLS	ordered	all	0.02
		3+ ADLS	ordered	all	0.03
	IADL Status	no IADLs	ordered	all	0.89
		1 IADL	ordered	all	0.06
		2+ IADLs	ordered	all	0.04
LFP & Benefits	Employment Status	out of labor force	prevalence	all	0.26
		unemployed	prevalence	all	0.06
		part time	prevalence	all	0.18
		full time	prevalence	all	0.50
	SS benefit receipt		biennial incidence	eligible & not receiving	
	DI benefit receipt		prevalence	eligible & age < 65	0.03
	Any health insurance		prevalence	age < 65	0.83
	SSI receipt		prevalence	all	0.02
Family	Marital status	single	prevalence	all	0.28
		cohabitating	prevalence	all	0.09
		married	prevalence	all	0.63
	Childbearing	no children	biennial incidence	female	0.91
		1 child	biennial incidence	female	0.09
		2 children	biennial incidence	female	0.00
Financial Resources ($K 2009)	financial wealth		median	all non-zero wealth	57.96
	earnings		median	working full time	17.87
	earnings		median	working part time	40.32
	wealth non-zero		prevalence	all	0.95

Table 5: Outcomes in the transition model. Estimation sample is PSID 1999-2013 waves.

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

Table 6: Restrictions on transition model. ✓indicates that an outcome at time $T-1$ is allowed in the transition model for an outcome at time T.

Control variable	Mean	Standard deviation	Minimum	Maximum
Non-hispanic black	0.112	0.315	0	1
Hispanic	0.127	0.333	0	1
Single	0.343	0.475	0	1
Cohabitating	0.0540	0.226	0	1
Married	0.603	0.489	0	1
Less than high school	0.133	0.340	0	1
High school/GED/some college/AA	0.549	0.498	0	1
College graduate	0.213	0.409	0	1
More than college	0.105	0.307	0	1
Doctor ever - heart disease	0.141	0.348	0	1
Doctor ever - hypertension	0.256	0.436	0	1
Doctor ever - stroke	0.0302	0.171	0	1
Doctor ever - chronic lung disease	0.0675	0.251	0	1
Doctor ever - cancer	0.0537	0.225	0	1
Doctor ever - diabetes	0.0907	0.287	0	1
Doctor ever - depression	0.0286	0.167	0	1
Never smoked	0.473	0.499	0	1
Former smoker	0.347	0.476	0	1
Current smoker	0.180	0.384	0	1
No ADL limitations	0.866	0.341	0	1
1 ADL limitation	0.134	0.341	0	1
2 ADL limitations	0	0	0	0
3 or more ADL limitations	0	0	0	0
No IADL limitations	0.790	0.408	0	1
1 IADL limitation	0.210	0.408	0	1
2 or more IADL limitations	0	0	0	0
$25 < \text{BMI} < 30$	0.373	0.484	0	1
$30 < \text{BMI} < 35$	0.186	0.389	0	1
$35 < \text{BMI} < 40$	0.0719	0.258	0	1
$\text{BMI} > 40$	0.0477	0.213	0	1
Any Social Security income LCY	0.200	0.400	0	1
Any Disability income LCY	0.0388	0.193	0	1
Any Supplemental Security Income LCY	0.0189	0.136	0	1
Any health insurance LCY	0.876	0.329	0	1
Out of labor force	0.318	0.466	0	1
Unemployed	0.0618	0.241	0	1
Working part-time	0.176	0.381	0	1
Working full-time	0.444	0.497	0	1
Earnings in 1000s capped at 200K	34.00	40.03	0	200
Wealth in 1000s capped at 2 million	270.1	457.2	-1974	2000

Table 7: Desciptive statistics for variables in 2009 PSID ages 25+ sample used as simulation stock population

Covariate	Education level	Partnered	Partnership type	Weight status	Smoking status	Hypertension	In labor force	Number of biological children
Non-hispanic black	-0.32	-0.76	-0.60	0.37	-0.38	0.23	0.14	0.39
Hispanic	-0.05	0.00	-0.15	0.28	-0.53	-0.06	-0.08	0.23
Male	-0.24	0.02	-0.14	0.11	0.25	0.13	0.48	-0.34
Less than HS/GED	0.00	0.03	0.25	0.04	0.74	0.09	-0.29	-0.19
College	0.00	-0.24	-0.21	-0.38	-0.72	-0.18	0.27	-0.19
Beyond college	0.00	-0.40	-0.54	-0.67	-1.05	-0.37	-0.06	0.03
R's mother less than high school	-0.32	-0.17	-0.04	0.00	0.00	0.00	-0.01	0.21
R;s mother some college	0.31	-0.11	0.18	0.00	0.00	0.00	-0.04	-0.17
R's mother college graduate	0.58	-0.17	0.11	0.00	0.00	0.00	0.04	-0.35
R's father less than high school	-0.15	-0.06	0.02	0.00	0.00	0.00	-0.02	0.02
R;s father some college	0.31	-0.16	0.11	0.00	0.00	0.00	0.03	-0.30
R's father college graduate	0.71	-0.07	0.14	0.00	0.00	0.00	-0.06	-0.44
Poor as a child	-0.20	0.00	-0.07	0.00	0.00	0.00	-0.10	0.13
Wealthy as a child	-0.06	-0.07	-0.09	0.00	0.00	0.00	-0.03	0.09
Fair or poor health before age 17	-0.18	-0.14	-0.07	0.00	0.00	0.00	-0.20	-0.00
Age 25 or 26	-0.16	-0.20	-0.24	-0.09	-0.05	-0.13	-0.06	-0.26
Constant	1.46	0.98	0.84	0.37	0.12	-1.71	0.98	0.49

Table 8: Parameter estimates for latent model: conditional means and thresholds. Sample is respondents age 25-30 in 2005-2011 PSID waves

	Education level	Partnered	Partnership type	Weight status	Smoking status	Hypertension	In labor force	Number of biological children
Education level	1.000							
Partnered	0.141	1.000						
Partnership type	0.299	0.000	1.000					
Weight status	0.116	0.019	0.076	1.000				
Smoking status	0.004	-0.124	-0.187	-0.021	1.000			
Hypertension	0.055	-0.077	0.088	0.300	0.009	1.000		
In labor force	0.036	-0.130	-0.031	-0.006	-0.004	-0.006	1.000	
Number of biological children	-0.389	0.274	0.144	0.001	-0.004	0.024	-0.186	1.000

Table 9: Parameter estimates for latent model: parameterized covariance matrix. Sample is respondents age 25-30 in 2005-2011 PSID waves

Year	Hypertension	Overweight	Obese 1	Obese 2	Obese 3	Never Smoked	Former Smoker	Current Smoker
2009	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2010	1.00	1.00	1.04	1.01	1.01	1.00	1.00	0.99
2011	1.00	1.00	1.07	1.01	1.03	1.01	0.99	0.98
2012	1.00	1.00	1.09	1.01	1.04	1.01	0.99	0.98
2013	1.00	1.00	1.11	1.02	1.06	1.01	0.99	0.97
2014	1.00	1.00	1.14	1.02	1.07	1.02	0.98	0.96
2015	1.00	1.01	1.16	1.03	1.08	1.02	0.98	0.95
2016	1.00	1.02	1.19	1.03	1.10	1.03	0.98	0.94
2017	0.99	1.05	1.21	1.04	1.11	1.03	0.97	0.94
2018	0.98	1.09	1.23	1.05	1.13	1.03	0.97	0.93
2019	0.98	1.09	1.25	1.06	1.14	1.04	0.97	0.92
2020	0.98	1.10	1.27	1.08	1.16	1.04	0.96	0.91
2021	0.98	1.09	1.29	1.09	1.17	1.04	0.96	0.91
2022	0.98	1.08	1.31	1.11	1.19	1.05	0.95	0.90
2023	0.98	1.07	1.33	1.13	1.20	1.05	0.95	0.89
2024	0.98	1.06	1.35	1.15	1.22	1.05	0.95	0.88
2025	0.98	1.04	1.37	1.18	1.24	1.06	0.94	0.87
2026	0.98	1.02	1.40	1.21	1.25	1.06	0.94	0.87
2027	1.00	0.99	1.43	1.24	1.27	1.06	0.94	0.86
2028	1.03	0.97	1.47	1.26	1.28	1.07	0.93	0.85
2029	1.04	0.95	1.51	1.27	1.30	1.07	0.93	0.84
2030	1.04	0.95	1.51	1.27	1.30	1.07	0.93	0.84
2031	1.04	0.95	1.51	1.27	1.30	1.07	0.93	0.84
2032	1.04	0.95	1.51	1.27	1.30	1.07	0.93	0.84
2033	1.04	0.95	1.51	1.27	1.30	1.07	0.93	0.84
2034	1.04	0.95	1.51	1.27	1.30	1.07	0.93	0.84
2035	1.04	0.95	1.51	1.27	1.30	1.07	0.93	0.84

Table 10: Health and risk factor trends for replenishing cohorts, prevalences relative to 2009

Year	Less than HS	HS Grad	College Grad	Graduate School
2009	1.00	1.00	1.00	1.00
2010	0.98	0.99	1.02	1.04
2011	0.96	0.98	1.03	1.08
2012	0.93	0.97	1.05	1.12
2013	0.91	0.96	1.06	1.17
2014	0.89	0.95	1.08	1.21
2015	0.87	0.94	1.09	1.26
2016	0.85	0.93	1.11	1.31
2017	0.83	0.92	1.12	1.36
2018	0.81	0.91	1.14	1.41
2019	0.79	0.90	1.15	1.46
2020	0.77	0.88	1.16	1.51
2021	0.75	0.87	1.18	1.57
2022	0.73	0.86	1.19	1.63
2023	0.71	0.85	1.20	1.68
2024	0.69	0.84	1.21	1.74
2025	0.67	0.83	1.23	1.80
2026	0.66	0.81	1.24	1.87
2027	0.64	0.80	1.25	1.93
2028	0.62	0.79	1.26	1.99
2029	0.60	0.78	1.27	2.06
2030	0.60	0.78	1.27	2.06
2031	0.60	0.78	1.27	2.06
2032	0.60	0.78	1.27	2.06
2033	0.60	0.78	1.27	2.06
2034	0.60	0.78	1.27	2.06
2035	0.60	0.78	1.27	2.06

Table 11: Education trends for replenishing cohorts, prevalences relative to 2009

Year	No Children	One Child	Two Children	Three Chidren	Four or More Children	Partnered	Married
2009	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2010	1.01	1.00	0.99	0.98	0.98	1.00	0.98
2011	1.01	0.99	0.98	0.97	0.95	0.99	0.96
2012	1.02	0.99	0.97	0.95	0.93	0.99	0.94
2013	1.03	0.98	0.96	0.93	0.90	0.99	0.91
2014	1.03	0.98	0.95	0.91	0.88	0.99	0.89
2015	1.04	0.97	0.94	0.90	0.86	0.98	0.87
2016	1.05	0.97	0.92	0.88	0.84	0.98	0.85
2017	1.05	0.96	0.91	0.87	0.82	0.98	0.82
2018	1.06	0.95	0.90	0.85	0.79	0.98	0.80
2019	1.07	0.95	0.89	0.83	0.77	0.98	0.78
2020	1.07	0.94	0.88	0.82	0.75	0.98	0.76
2021	1.08	0.94	0.87	0.80	0.73	0.98	0.73
2022	1.09	0.93	0.86	0.79	0.72	0.97	0.71
2023	1.09	0.93	0.85	0.77	0.70	0.97	0.69
2024	1.10	0.92	0.84	0.76	0.68	0.97	0.66
2025	1.11	0.92	0.83	0.75	0.66	0.97	0.64
2026	1.11	0.91	0.82	0.73	0.64	0.98	0.62
2027	1.12	0.90	0.81	0.72	0.63	0.98	0.60
2028	1.13	0.90	0.80	0.70	0.61	0.98	0.57
2029	1.13	0.89	0.79	0.69	0.59	0.98	0.55
2030	1.13	0.89	0.79	0.69	0.59	0.98	0.55
2031	1.13	0.89	0.79	0.69	0.59	0.98	0.55
2032	1.13	0.89	0.79	0.69	0.59	0.98	0.55
2033	1.13	0.89	0.79	0.69	0.59	0.98	0.55
2034	1.13	0.89	0.79	0.69	0.59	0.98	0.55
2035	1.13	0.89	0.79	0.69	0.59	0.98	0.55

Table 12: Social trends for replenishing cohorts, prevalences relative to 2009

	2001			2007			2013		
	THEMIS	PSID		THEMIS	PSID		THEMIS	PSID	
Outcome	mean	mean	p	mean	mean	p	mean	mean	p
Died	0.019	0.018	0.865	0.017	0.023	0.019	0.023	0.031	0.005

Table 13: Crossvalidation of 1999 cohort: Mortality in 2001, 2007, and 2013

	2001			2007			2013		
	THEMIS	PSID		THEMIS	PSID		THEMIS	PSID	
Outcome	mean	mean	p	mean	mean	p	mean	mean	p
Age on July 1st	48.888	49.022	0.552	53.573	53.379	0.394	57.849	57.819	0.892
Black	0.100	0.093	0.096	0.098	0.087	0.014	0.098	0.092	0.261
Hispanic	0.079	0.078	0.836	0.081	0.085	0.386	0.085	0.095	0.046
Male	0.456	0.460	0.516	0.453	0.463	0.181	0.450	0.458	0.344

Table 14: Crossvalidation of 1999 cohort: Demographic outcomes in 2001, 2007, and 2013

	2001			2007			2013		
	THEMIS	PSID		THEMIS	PSID		THEMIS	PSID	
Outcome	mean	mean	p	mean	mean	p	mean	mean	p
Any ADLs	0.072	0.064	0.036	0.029	0.126	0.000	0.030	0.138	0.000
Any IADLs	0.304	0.113	0.000	0.085	0.130	0.000	0.094	0.168	0.000
Cancer	0.036	0.035	0.628	0.066	0.057	0.011	0.096	0.090	0.154
Diabetes	0.065	0.062	0.316	0.103	0.092	0.010	0.147	0.131	0.007
Heart Disease	0.098	0.106	0.091	0.140	0.152	0.028	0.183	0.171	0.063
Hypertension	0.181	0.172	0.108	0.286	0.264	0.002	0.388	0.364	0.004
Lung Disease	0.037	0.039	0.474	0.063	0.058	0.168	0.089	0.090	0.816
Stroke	0.020	0.020	0.857	0.031	0.032	0.722	0.044	0.039	0.078

Table 15: Crossvalidation of 1999 cohort: Binary health outcomes in 2001, 2007, and 2013

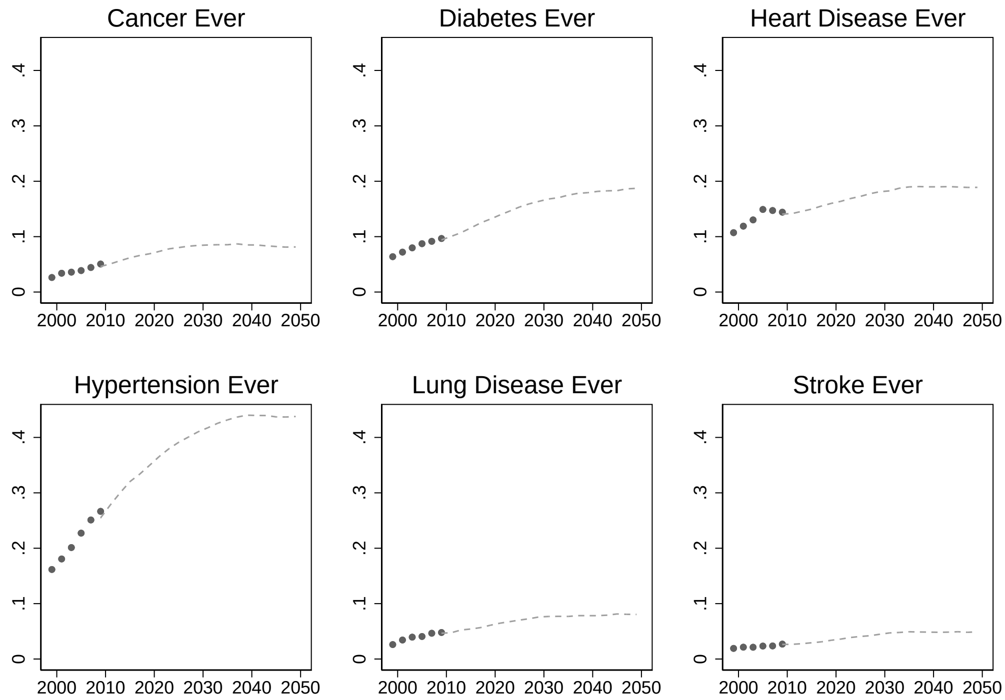

Figure 3: Historic and forecasted chronic disease prevalence for men ages 25+

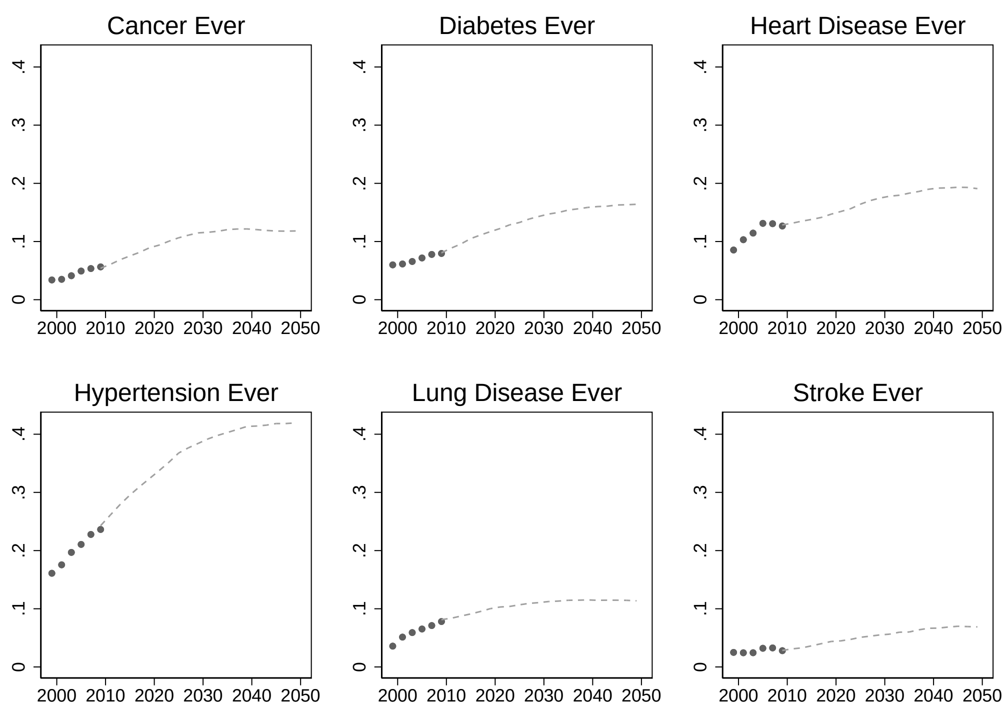

Figure 4: Historic and forecasted chronic disease prevalence for women ages 25+

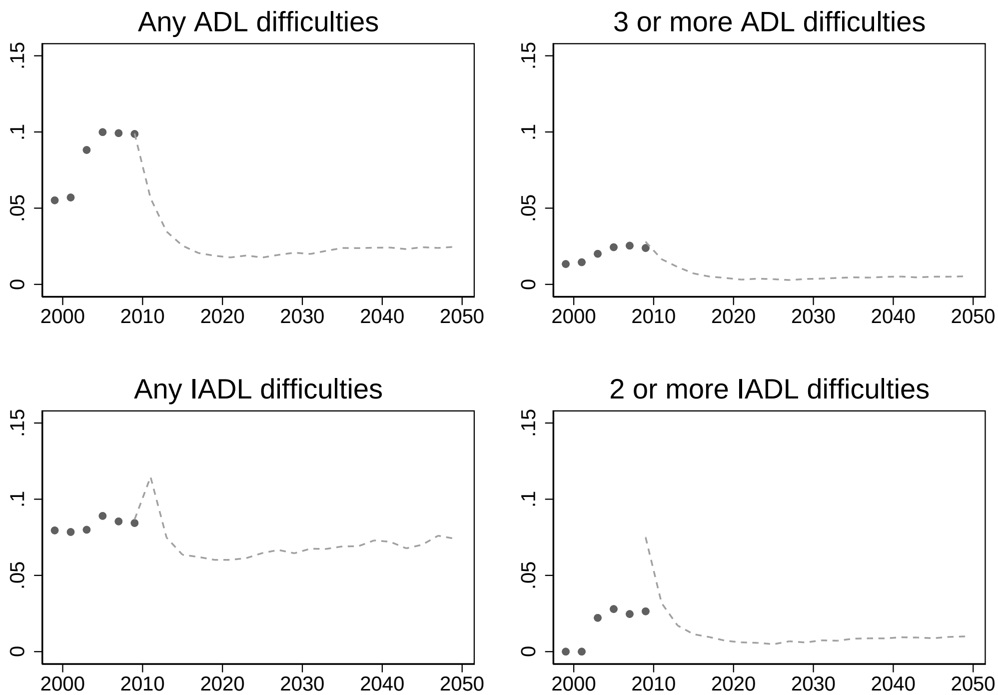

Figure 5: Historic and forecasted ADL and IADL prevalence for men ages 25+

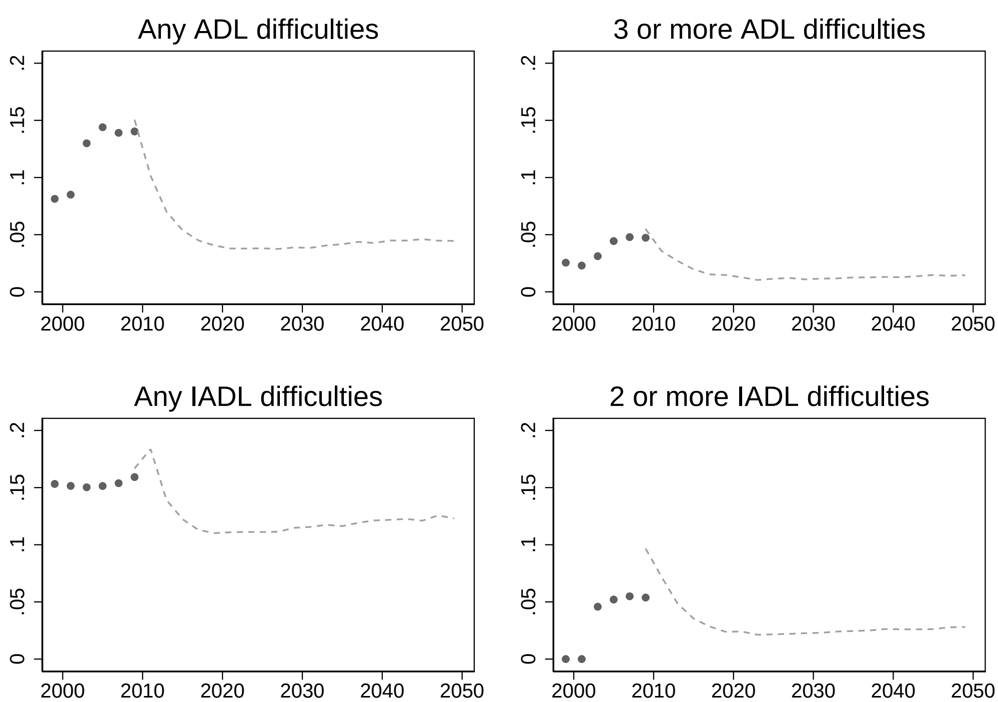

Figure 6: Historic and forecasted ADL and IADL prevalence for women ages 25+

	2001			2007			2013		
	THEMIS	PSID		THEMIS	PSID		THEMIS	PSID	
Outcome	mean	mean	p	mean	mean	p	mean	mean	p
BMI	27.351	27.342	0.910	27.962	28.036	0.413	28.404	28.338	0.513
Current smoker	0.202	0.200	0.789	0.202	0.167	0.000	0.202	0.147	0.000
Ever smoked	0.471	0.513	0.000	0.463	0.525	0.000	0.454	0.531	0.000

Table 16: Crossvalidation of 1999 cohort: Risk factor outcomes in 2001, 2007, and 2013

	2001			2007			2013		
	THEMIS	PSID		THEMIS	PSID		THEMIS	PSID	
Outcome	mean	mean	p	mean	mean	p	mean	mean	p
Claiming SSDI	0.018	0.023	0.009	0.017	0.033	0.000	0.021	0.049	0.000
Claiming OASI	0.182	0.192	0.091	0.220	0.218	0.763	0.290	0.279	0.154
Claiming SSI	0.016	0.016	0.646	0.016	0.016	0.705	0.014	0.017	0.127
Working for pay	0.606	0.683	0.000	0.618	0.657	0.000	0.587	0.602	0.071

Table 17: Crossvalidation of 1999 cohort: Binary economic outcomes in 2001, 2007, and 2013

Covariate	Model I	Model II	Model III	Model IV	Model V
ADL limitation	-0.3231***	-0.2542***	-0.2495***	-0.1956***	-0.1950***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ever diagnosed with cancer		-0.0324***	-0.0351***	-0.0139***	-0.0116**
		(0.000)	(0.000)	(0.000)	(0.002)
Ever diagnosed with diabetes		-0.0574***	-0.0529***	-0.0204***	-0.0220***
		(0.000)	(0.000)	(0.000)	(0.000)
Ever diagnosed with high blood pressure		-0.0560***	-0.0497***	-0.0283***	-0.0281***
		(0.000)	(0.000)	(0.000)	(0.000)
Ever diagnosed with heart disease		-0.0571***	-0.0560***	-0.0291***	-0.0293***
		(0.000)	(0.000)	(0.000)	(0.000)
Ever diagnosed with lung disease		-0.0462***	-0.0391***	-0.0202***	-0.0171***
		(0.000)	(0.000)	(0.000)	(0.000)
Ever diagnosed with stroke		-0.0601***	-0.0579***	-0.0340***	-0.0340***
		(0.000)	(0.000)	(0.000)	(0.000)
Obese(BMI≥30)			-0.0277***	-0.0168***	-0.0170***
			(0.000)	(0.000)	(0.000)
Current smoker			-0.0534***	-0.0381***	-0.0388***
			(0.000)	(0.000)	(0.000)
Single			-0.0018	0.0001***	-0.0007
			(0.163)	(0.000)	(0.564)
Widowed			-0.0370***	-0.0208***	-0.0148***
			(0.000)	(0.000)	(0.000)
Very good self-reported health * age < 75				-0.0239***	-0.0229***
				(0.000)	(0.000)
Good self-reported health * age < 75				-0.0615***	-0.0611***
				(0.000)	(0.000)
Fair self-reported health * age < 75				-0.1518***	-0.1515***
				(0.000)	(0.000)
Poor self-reported health * age < 75				-0.2743***	-0.2737***
				(0.000)	(0.000)
Self-reported health PSID/MEPS * age≥75				-0.0224***	-0.0223***
				(0.000)	(0.000)
Male					0.0186***
					(0.000)
Non-hispanic black					0.0056**
					(0.002)
Hispanic					0.0142***
					(0.000)
Constant	0.8870***	0.9136***	0.9326***	0.9622***	0.9504***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	70721	70310	70310	630600704	70310
R^2	0.08	0.15	0.18	0.28	0.29
* p < 0.05, ** $p < 0.01$, *** $p < 0.001$					

Table 18: OLS regressions of EQ-5D utility index among individuals in the MEPS 2001–2003. p-values in parentheses. Data source: MEPS 2001–2003. EQ-5D scoring algorithm is based on Shaw et al. (2005).

Covariate	EQ-5D
One IADL limitation	-0.0503***
	(0.000)
Two or more IADL limitations	0.0000
	(.)
One ADL limitation	-0.0859***
	(0.000)
Two ADL limitations	0.0000
	(.)
Three or more ADL limitations	0.0000
	(.)
Ever diagnosed with cancer	-0.0222***
	(0.000)
Ever diagnosed with mood disorders	-0.0178***
	(0.000)
Ever diagnosed with diabetes	-0.0465***
	(0.000)
Ever diagnosed with heart disease	-0.0442***
	(0.000)
Ever diagnosed with high blood pressure	-0.0395***
	(0.000)
Ever diagnosed with lung disease	-0.0476***
	(0.000)
Ever diagnosed with stroke	-0.0664***
	(0.000)
Current smoker	-0.0528***
	(0.000)
Obese(BMI$\geq$30)	-0.0279***
	(0.000)
Single	-0.0014**
	(0.004)
Widowed	-0.0147***
	(0.000)
Constant	0.9333***
	(0.000)
N	78941
R^2	0.64
* p $<$ 0.05, ** $p < 0.01$, *** $p < 0.001$	

Table 19: OLS regression of the predicted EQ-5D index score against chronic conditions and THEMIS-type functional status specification. p-values in parentheses. Data source: PSID, 1999–2013. EQ-5D score was predicted using Model IV in Table 18.

Year	Census 25+	THEMIS Minimal 25+	Census 65+	THEMIS Minimal 65+
2009	202.1	202.0	39.6	39.4
2011	206.6	205.6	41.4	40.6
2013	211.0	209.1	44.7	43.4
2015	215.9	213.7	47.7	46.8
2017	220.9	218.3	50.8	50.0
2019	225.5	222.3	54.2	52.6
2021	229.8	225.9	57.7	55.5
2023	233.9	229.3	61.4	58.1
2025	238.0	232.4	65.1	61.5
2027	241.9	234.8	68.4	64.3
2029	245.7	237.2	71.4	67.1
2031	249.3	239.1	73.8	68.8
2033	252.9	240.9	75.5	69.0
2035	256.0	242.4	77.3	70.4
2037	259.2	243.9	78.8	70.3
2039	262.6	245.4	79.4	69.5
2041	265.8	246.9	79.9	68.5
2043	269.0	248.2	80.4	68.3
2045	272.2	249.6	81.3	68.4
2047	275.3	251.2	82.2	68.3
2049	278.4	252.7	83.2	67.7

Table 20: Population forecasts: Census compared to Simulation

References

Atherly, A., Dowd, B. E., and Feldman, R. (2004). The effect of benefits, premiums, and health risk on health plan choice in the medicare program. *Health services research*, 39(4p1):847–864.

Board of Trustees of the Federal Insurance and Federal Supplementary Insurance Funds (2006). 2006 annual report of the board of trustees of the federal insurance and federal supplementary insurance funds. Technical report, Board of Trustees of the Federal Insurance and Federal Supplementary Insurance Funds, Washington, DC.

Board of Trustees of the Federal Insurance and Federal Supplementary Insurance Funds (2007). 2007 annual report of the board of trustees of the federal insurance and federal supplementary insurance funds. Technical report, Board of Trustees of the Federal Insurance and Federal Supplementary Insurance Funds, Washington, DC.

Buchmueller, T. (2006). Price and the health plan choices of retirees. *Journal of Health Economics*, 25(1):81–101.

Dolan, P. (1997). Modeling valuations for euroqol health states. *Medical care*, 35(11):1095–1108.

Fryback, D. G., Dunham, N. C., Palta, M., Hanmer, J., Buechner, J., Cherepanov, D., Herrington, S., Hays, R. D., Kaplan, R. M., Ganiats, T. G., et al. (2007). Us norms for six generic health-related quality-of-life indexes from the national health measurement study. *Medical care*, 45(12):1162–1170.

Goldman, D. P., Shekelle, P. G., Bhattacharya, J., Hurd, M., and Joyce, G. F. (2004). Health status and medical treatment of the future elderly. Technical report, DTIC Document.

MacKinnon, J. G. and Magee, L. (1990). Transforming the dependent variable in regression models. *International Economic Review*, pages 315–339.

Roodman, D. (2011). Fitting fully observed recursive mixed-process models with cmp. *Stata Journal*, 11(2):159–206(48).

Shaw, J. W., Johnson, J. A., and Coons, S. J. (2005). Us valuation of the eq-5d health states: development and testing of the d1 valuation model. *Medical care*, 43(3):203–220.

Smith, K. and Favreault, M. (2013). A primer on modeling income in the near term, version 7. Technical report, The Urban Institute.

The Congressional Budget Office (2009). CBOs long-term model: An overview. Technical report, The Congressional Budget Office, Washington, D.C.