Social Security Forecasts and the Future Health of the American Population[*]

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1.0   Introduction

Accurately forecasting expenditures on Social Security is a difficult endeavor because doing so requires predicting the health status of Americans well into the future. While health forecasting has understandably received more attention in predictions of future Medicare expenditures – health care expenditures are more directly tied to health – such forecasts are crucial for Social Security forecasting as well. First, the extent of Social Security expenditures on retirees and their spouses (Old-Age and Survivors Insurance, or OASI) depends on how long people survive into their retirement years, and this in turn depends critically on their health status. A healthier, more long-lived population will spend more on OASI in the long run. Second, both Supplemental Security Income (SSI) and Social Security Disability Income (DI) payments, though less in aggregate than OASI payments, depend even more critically on population health status.

Forecasts that ignore changes in population health status – or inadequately model them – are thus bound to be inaccurate. This is especially the case since the health status of Americans has been rapidly changing over the last decades, for both better and worse. There is considerable evidence, for instance, that newer cohorts of elderly Americans have become healthier than previous cohorts with declining rates of disability (Manton, Gu, and Lamb, 2006). Rates of smoking and the cancers that it causes have also declined, which makes the population as a whole healthier. At the same time, obesity rates and many chronic diseases associated with it have increased throughout the population, including in particular the near-elderly. As these populations age toward retirement, they are likely to have shorter lives, on average, than cohorts of elderly that came before them (Olshansky et al, 2005;). At the same time, prominent demographers have criticized the Social Security Administration for being too pessimistic about future trends in mortality (Soneji and King, 2012). Disentangling these competing trends and claims requires a sophisticated approach to disease and mortality modeling.

In this paper, we apply an updated version of the Future Elderly Model, which has been used extensively over the last decade to forecast future Medicare expenditures and to answer counterfactual questions about the effects of changing medical technology on future medical expenditures, to the purpose of predicting future expenditures by the Social Security Administration. At the core of the FEM is a detailed microsimulation that captures a diverse set

of health conditions and demographic factors known to drive health care spending and mortality. The parameters underlying the FEM are estimated using large nationally-representative longitudinal databases, including the Health and Retirement Study (HRS) and the Medical Expenditure Panel Survey (MEPS). The FEM provides detailed forecasts for cohorts of Americans 51 years old and above.[1] One key feature of the FEM is its ability to handle the problem of competing risks, where declines in the mortality associated one condition (or increases in the prevalence of that condition) lead mechanically to increases in the mortality and prevalence of other conditions (since dead people cannot develop any new chronic diseases). Our focus in this paper, in addition to introducing the predictions of the FEM on outcomes relevant to the Social Security Administration, is on delineating how alternate assumptions changes in mortality forecasts affect forecasts.

2.0 Social Security Forecasting—An Overview

There is no such thing as the perfect forecasting tool. Every forecasting approach necessarily emphasizes some parts of the complicated reality that will determine the future of Medicare, while deemphasizing others. The right question to ask in assessing a forecasting tool is whether it accomplishes the goals for which it was designed. We do not have the space in this paper to provide a comprehensive review of all the approaches that have been taken to forecasting Social Security expenditures. Instead, we will briefly discuss the approach taken by the Social Security Administration (SSA) to highlight the key issue of mortality rate forecasting.

All forecasts depend in large part on unverifiable assumptions about the future. The accuracy and usefulness of a forecasting framework depends critically on two things: the truth of the conceptual model that drives the forecast and the fidelity of the parameter estimates. Since all models are necessarily simplifications, the assumptions made in the construction of a forecasting model focus attention on those aspects of underlying reality of most interest to the designers of the model and the consumers of its forecasts. These assumptions also limit the set

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[1] The restriction to people 51 years old and above is required by reliance on HRS data, which does not sample people younger than that.

of counterfactual questions that can be addressed using the model. The SSA's primary framework is designed to answer one counterfactual question in particular -- "What would happen to Social Security expenditures if life expectancies improved at a slower (or faster) rate?"

2.1 Office of the Actuary Forecasting

The Social Security Office of the Actuary (OACT) each year produces updated projections of future Social Security expenditures on the basis of a sophisticated demographic model that accounts for a wide variety of important changes in the American population. In particular, the OACT model accounts for trends in fertility, immigration, and mortality. In addition, the model applies forecasts future changes in unemployment, inflation, interest rates, wages, and disability to predict both Social Security expenditures and income (Cheng et al., 2004; Soneji and King, 2012). The OACT model accounts for changes in the age-, sex-, and cause-specific death mortality rates for heart disease, cancer, vascular disease, violence, respiratory diseases, diabetes mellitus, and a residual category of all other causes. The modeling effort includes an exercise to determine how sensitive forecasted expenditures and receipts are to variations in the parameters that underlie the model (Burdick and Manchester, 2003).

One of the key parameter inputs into the SSA model involves a forecast of how secular mortality rates will change over the upcoming decades. The forecast necessarily requires considerable guesswork since it involves predicting how (in the context of the SSA model) medical technology will change cause-specific death rates. The basic idea behind this forecast is to use historical data on improvements in mortality as a way to ground future expectations. The SSA intermediate forecast assumption effectively assumes that future improvements in the mortality rate will mirror those that the US experienced between 1900 and the present (Soneji and King, 2012; Lee and Carter, 1992). This is a vital parameter because small changes in future mortality rates will have an outsized impact on future Social Security outlays. A long-lived future population will stay alive longer and thus be eligible for OASI or other benefits for a longer period of time.

While the OACT methodology flexibly models how changes in mortality leads to changes in future Social Security outlays and taxes, demographers have criticized the model for the arbitrary way that it handles age- and cause specific mortality profiles. These profiles are only partly derived from nationally representative data sources, and in fact are modified ex-post by the Social Security Administration to make the numbers appear more "reasonable." Soneji and King (2012) argue that these arbitrary ex-post adjustments lead to a likely overestimate of future death rates.

Others have argued that the model's assumptions about forecasted mortality rate improvements are too pessimistic for other reasons. This criticism is partially based on the observation that cause-specific mortality rates have declined faster in the second half of the 20th Century than they did in the first half (Lee and Carter, 1992). By contrast, some economists have argued that technological progress in medicine is self-limiting, and that periods of great advances are followed by periods of slow improvement because after great progress, patients have less incentive to participate in randomized trials (Malani and Philipson, 2011). Whatever the case, our approach in this paper – similar to the one taken in the SSA modeling effort – is to run the FEM under alternate assumptions about future reductions in cause-specific mortality spanning from no future technological advances to substantial advances consistent with Social Security's intermediate scenario.

2.2   How the FEM Differs from the SSA Forecasting Methodology

The FEM is in some ways similar to the SSA forecasting methodology in that it forecasts how particular population subgroups – defined based on health status and demography – will evolve over the next decades. However, there are some important differences in emphasis that distinguish it from the SSA model:

- The FEM is a microsimulation model that permits a rich definition of population cells. Practically this means, for instance, that the FEM does not lump people into 5-year age bins and considers many covariate interactions in its cell definitions beyond the age-sex-cause of death cells considered in the SSA model.

- The FEM explicitly models and focuses attention on the competing risks problem, whereby decreases in the mortality rate associated with a particular disease tends to increase the prevalence of all other diseases (since a dead person cannot contract a new disease). This stands in contrast to the SSA forecasting model, which has come under criticism for inadequately addressing this problem (Wilmouth, 1995; Wilmouth, 2005).

- The FEM explicitly models disease prevalence and the transition between health states, in addition to state-specific mortality rates. The FEM framework permits a natural way of modeling risk-factors such as smoking and obesity that partly determine health status transitions. Unlike the Future Elderly Model, the OACT model does not explicitly track the prevalence of these conditions in the population, nor does it forecast changes in the prevalence of these conditions (and thus their effect on predicted Social Security outlays).

- In the FEM, new entrants in the model in each future year reflect observed health status trends in the population.

- The FEM emphasizes transparency in the estimation and application of model parameters, including health status transitions, conditional mortality regressions, and other outcomes, including Social Security outcomes. All of these parameters are based on regressions using high quality nationally representative datasets of the age 51+ population in the US, such as the Health and Retirement Study. All the regression parameters underlying the model are publicly available and a publicly released version of the FEM is freely available to anyone.

We conclude this section by noting an important weakness of the FEM relative to the Social Security model – the FEM only models people who are 51 years old and older. This is because the model relies heavily on the HRS data for its parameter estimates, and the HRS in turn only surveys people who are 51 years and older. A second important caveat is that the current version of the FEM forecasts only future Social Security outlays, not tax receipts. There are plans to extend the FEM to produce tax receipt outcomes, but that work has not yet been completed.

3.0   Trends in Elderly Health

To make the case that a more sophisticated approach to modeling health status trends in the American population is needed in Social Security forecasting, we survey here the epidemiological literature on trends in the health status of the elderly population. The main message of this literature seems to be mixed – some indicators point to a future elderly population that will be healthier than the current cohort of American elderly citizens, while other indicators point to a less healthy future elderly population. Our case for the Future Elderly Model rests in part on its ability to sort out the empirical importance of these indicators and produce a forecast that accounts for all of these conflicting trends.

3.1   Trends in Disability Rates Among the Elderly

It is widely-accepted that American elderly are less likely to be disabled than they were two decades ago (Freedman, Martin, and Schoeni 2002). The importance of these positive trends to the well-being of elderly populations should be obvious. This fact also represents a sharp reversal from the consensus among researchers developed in the 1970s that disability rates among the elderly were rising. To these researchers (for example, Gruenberg 1977), the impressive mortality declines of the 20th century represented a "failure of success" since it seemed that extra life years were spent by the elderly in a disabled state.

Though everyone has some intuitive idea about what it means to be disabled, when examined closely, disability turns out to be a hard concept to define-and hence difficult to measure in population based surveys. Generally, survey data reporting disabilities refer to two broad areas--functional limitations and work limitations. The former encompasses the most basic, mechanically-oriented activities of daily living (ADLs) such as dressing, eating, and bathing, as well as instrumental activities of daily living (IADLs) that involve everyday behaviors requiring a higher level of cognitive functioning than ADLs, such as grocery shopping, managing money, and preparing meals. All of the studies of disability surveyed in this section use one of these two definitions.

Manton, Corder, and Stallard (1997) use the 1982, '84, '89, and '94 National Long Term Care Surveys (NLTCS) to investigate trends in the prevalence of disability in the elderly population. Defining disability as an inability to perform an ADL/IADL without aid for at least 90 days, they find that the age-adjusted prevalence of disability for 1994 decreased by 3.6% from 1982 (from 24.9% to 21.3%). The authors compare the size of observed disabled population with that which would have occurred without the apparent declines in disability. There were 0.54 million and 1.2 million fewer disabled in 1989 and 1994, respectively, than there would have been had the 1982 rates stayed fixed (Manton, Corder, and Stallard 1993, 1997) Manton and Gu (2001) and Manton, Gu and Lamb (2004) update the results of Manton, Corder, and Stallard (1997) using the later waves of the NLTCS. They confirm a continuing decline in disability among the elderly, especially among the oldest age groups.

Freedman and Martin (1998) use the 1984 and 1993 Surveys of Income and Program Participation (SIPP) to investigate trends in disability prevalence. Their definition is of disability differs mildly from the one Manton and his colleagues use; they define it as difficulty seeing words in a newspaper, lifting and carrying 10 pounds, climbing stairs, or walking a quarter mile. The authors find that prevalence for difficulty in each category declined over the study period. Prevalence estimates ranged from 15.3% (difficulty seeing words in a newspaper) to 25.8% (walking ¾ mile) in 1984 to 11.6% to 22.3% for the same categories in 1993, a relative improvement of between 0.9% and 2.3% across functions.

Crimmins, Saito, and Reynolds (1997) use the Longitudinal Study of Aging (LSOA) (1984, '86, '88, '90) and the National Health Interview Survey (NHIS) (1982 to '93) to track the prevalence of disability over time. They confirm net decreases in disability from 1982 to 1993 despite intermediate fluctuations. Using NHIS 1970, '80, and '90 data and an alternate definition of disability (any limitation in usual activity over the past 12 months), Crimmins, Saito, and Ingegneri (1999) find fluctuations in long-term disability prevalence. Institutionalization rates have declined for most ages, but have stayed the same or increased above age 80. Long-term disability increased for the 60+ population from 1970 to 1980, but decreased from 1980 to 1990.

Crimmins, Saito, and Ingegneri (1999) also investigate the relative contributions to life expectancy of disability-free and disabled years. They use the NHIS definition of years of active life expectancy: the "years when an individual's health does not affect ability to perform normal activities of life including both major and secondary activities." At age 65, total life expectancy increased from 1970 to 1990, but the proportion of that increase that was due to disability free years was small. From 1970 to 1980, disability-free life expectancy did not increase, but there was a slight increase from 1980 to 1990. McKinlay et al. (1989) also find that disability-free life expectancy has decreased for newborns and middle-aged women from 1964 to 1985. These findings do not entirely support the hypothesis by Fries (1980) that active-life span is increasing faster than total life span.

3.2   Trends in Elderly Chronic Disease

Desai et al. (1999) report that the leading causes of death in the U.S. among those over 65 are heart disease (1,808/100,000 population), cancers (1,131/100,000 population), and strokes (415/100,000 population). The good news is that all three of these conditions have been declining in prevalence and associated mortality over the last decade. Unfortunately, there has been mixed news about other chronic health trends. While hypertension, heart disease, stroke, and cancer among the elderly incidence have declined in the past decade, there has been an increase in asthma, hip fractures, arthritis, diabetes, and obesity. While a comprehensive survey of disease trends is beyond our scope here, interested readers can consult Reynolds et al. (1998) or Crimmins et al. (1999).

Heart disease rates and mortality have declined in the past decade so much that it has inspired prominent newspaper articles such as Kolata (2003). Fang and Alderman (2002) report sharp declines between 1988 and 1997 in in-hospital mortality from myocardial infarction for all age groups, including the elderly. They attribute these declines to a 98% increase in angiography use and a 201% increase in revascularization procedures (for those over 75) during the period. Effectively, heart disease is changing from an acute condition resulting in near-immediate death to a chronic condition. For those with chronic heart failure, the news is good as well. Levy et al. (2002) report that both the incidence and mortality due to heart failure have fallen. McDonald et al. (2002) report that even for elderly patients with serious and hard to treat heart

conditions like ventricular arrhythmias, survival rates have been improving, though medical expenditures to treat this condition have been rising.

The CDC (2002d), using data from a nationally representative sample of patients tested for hypertension, reports that age-adjusted hypertension prevalence fell from 39.8% in 1971-1974 to 23.9% in 1988-1994. The same report however, shows that the prevalence of hypertension rates measured by self-reports rose by 6.7% (from 41.8% to 48.5%) between 1991 and 1999 among the elderly population. Psaty et al. (2002), on the other hand, reports that treatment rates for elderly with hypertension improved markedly between 1990 and 1999.

For the four most common types of cancer–lung, breast, prostate, and colorectal cancer–age adjusted mortality rates have fallen by an average of 2% per year for each year between 1990 and 1998 (CDC 2002e). These mortality rates have fallen even more precipitously for the elderly than for younger cohorts. Cancer incidence rates have also fallen during this same period, most sharply for men but also for women (Jemal et al. 2003). Much of this latter finding can be attributed to increased screening for prostate and breast cancer in the early 1990s.

Age adjusted mortality rates due to stroke have fallen in the past 100 years (Muntner et al. 2002). Much of this improvement can be attributed to advances in the treatment of stroke. That is, stroke incidence rates have not declined between 1980 and 1999 (Kennedy et al. 2002), but mortality rates have increased. Fang and Alderman (2001) find that age-adjusted hospitalization rates for stroke actually increased between 1988 and 1997. Stroke outcomes are better than they used to be, but at a cost in increased medical care use.

We turn next to the bad news. The Centers for Disease Control (2002a) report that the estimate annual prevalence rate for asthma (or an asthma attack or an episode of asthma) rose for the over 65 population from 31.9% in 1980 to and astonishing 45.5% in 1996. The largest increase took place between 1980 and 1985, when the asthma prevalence rate was 38.6%. The CDC constructed these estimates using data from the annual National Health and Interview Survey (NHIS), which was redesigned in 1997. Since the redesign, which changed the asthma assessment tool (and hence the measured asthma prevalence levels) asthma rates from the elderly in the NHIS have declined from 27.3% in 1997 to 22.1% in 1999. Mannino et al. (1998)

confirm that the asthma trends are not an artifact of the NHIS. Using three other nationally representative databases, they find increasing prevalence of self-reported asthma and increasing asthma death rates between 1960 and 1995. Using a community based survey in the UK as evidence, Parameswaran et al. (1998) argue that asthma is "under perceived" by the elderly, so these rates may actually underestimate the problem for seniors.

Hip fracture rates have risen sharply among the elderly. Samelson et al. (2002), using longitudinal data from the ubiquitous Framingham Heart Study, find that age standardized hip fracture rates are twice as common among men born between 1911 and 1921 as they were for men born between 1887 and 1900. There is a 40% increase for women in the hip fracture incidence rate in the more recent birth cohorts. Melton et al. (1998) using data from the Mayo clinic in Minnesota calculate that–for that community–hip fracture rates have risen from 135.8 per 100,000 residents between 1928-1942 to 612.7 per 100,000 between 1973-1992. The World Health Organization (1999) predicts that these trends will accelerate. The title of their report summarizes their prediction nicely: "Hip fractures to treble by the year 2030."

Arthritis is a major cause of disability in the U.S. (CDC, 2000). Comparing the CDC (2002b) report on the prevalence of arthritis in 2001 with the CDC (1994) report on its prevalence in 1990, it is clear that arthritis prevalence rose from 50.2% of the elderly population in 1990 to 58.8% in 2001. For the previous decade between 1982 and 1993, however, Crimmins et al. (1999) partly attribute the increased ability of those in their 60s to work to declines in the prevalence of arthritis.

It is well known that obesity rates have been rising in the U.S., not just over the past two decades, but indeed over the whole of the past century, and the elderly have not been excepted from this trend (Costa and Steckel 1995).   Lakdawalla, Bhattacharya, and Goldman (2004) using NHIS data find that obese elderly are nearly twice as likely to be disabled as their non-disabled counterparts. This is confirmed by the CDC (2002c) which, using another nationally representative data set, finds that 24% of obese seniors are disabled compared with 14.5% of non-disabled seniors. On the other hand, weight gain in old age correlates with reductions in mortality (see Newman et al. 2001), so obesity may be a mixed curse for the elderly.

Given the rise in obesity, it is no surprise that diabetes prevalence has risen among the elderly over the past two decades. The CDC (1997) reports that diabetes prevalence among the elderly rose from a low of roughly 80 cases per 1000 elderly in 1983 to over 100 cases per 1000 elderly in 1994. Bertoni et al.'s (2002) finding using Medicare claims files that elderly patients with diabetes have a 41% higher all-cause mortality rate than the general population is also not surprising. The CDC (2012) updates these numbers up through 2011 and finds that these trends have worsened in every state in the U.S.

4.0 Future Elderly Model

The FEM is a complicated model with many moving parts. We leave a full discussion of the details of the model for the *Appendix*. Here, we briefly describe the pieces of the model, how they fit together, and how the model has been used by researchers. The last may give the reader a sense of the range of counterfactual questions that could be addressed using the model, even though in this paper we focus only on mortality rate assumptions in Social Security forecasting.

4.1   A Brief Introduction to the FEM

The FEM simulation consists, first, of a population of individuals along with their health and demographic characteristics observed in a baseline year. The health and demographic characteristics of each individual generate their patterns of use and spending. To simulate future years' use and spending, the characteristics of the simulated population are evolved forward in time and future Social Security payments are simulated based on those characteristics.

The FEM tracks the presence of 8 chronic conditions (hypertension, heart disease, cancer, diabetes, stroke, chronic obstructive pulmonary disease, ADL and IADL disability, and obesity). Presence of a condition in a particular year is determined using the Medicare Claims by "looking back" a certain number of years in the claims data for a certain number of occurrences of the relevant codes, where the number of years and the number of occurrences vary by condition. The chronic conditions file contains both indicators for whether an enrollee qualified as having

each chronic condition this year and an indicator for whether he ever qualified as having each chronic condition.

Figure 1 shows the basic schema of the Future Elderly Model, in which a population of simulated people is aged forward over time. The population is evolved forward in time in two ways. First, people already in the population encounter transitions in their health and demographic states. They age one year each year. They contract new chronic conditions with a probability depending on their current characteristics. They die with a probability depending on their current characteristics. Second, new 51 year olds enter the population, "refreshing" it.

To construct the simulation model, we construct a <u>simulation</u> <u>sample</u> of individuals in our baseline year of 2006. Then we estimate transition probabilities between health states. Then we estimate the relationships between health states, demographics and the outcomes we want to forecast, including Social Security expenditures. Then we estimate the characteristics of incoming waves of 51 year olds and create these waves of entering cohorts in our simulation sample. To estimate health transition probabilities and the relationship between health states, demographics, use, and spending we use some <u>estimation</u> <u>sample</u>, which is not the same as the simulation sample.

To refresh the sample, we estimate the distribution of health characteristics in the newly eligible population and create new members of the population who have this distribution of characteristics. This is done using the simulation sample, which consists of information from the National Health Interview Survey and modified based on our review of the epidemiological literature (see Section 3). Trends in these factors are calculated and the prevalence of the chronic conditions for the newly eligible population are updated to reflect these trends and the expected effects of these trends based on the relevant epidemiological literature.

Finally, for each simulated person alive in each year of the simulation, we obtain a prediction of DI, SSI, or OASI benefit as well as amount received using a separate outcomes module. This module consists of regressions – using HRS data -- that estimate the benefit receipt probabilities and the expected amount of the transfer conditional on a rich set of health status

and demographic characteristics. Predictions from these regressions form the basis for FEM predictions of future Social Security participation and outlays.

4.2   Findings to Date from the FEM

The FEM has been used to project how changes in medical technology and demographic trends are likely to affect future health care expenditures, most prominently in a special issue of *Health Affairs* devoted to findings from the model. Perhaps the most salient policy implications of this research are: (1) Medicare faces substantial technological risk for high health care spending—at least on the order of the cost growth driven by demographic trends; (2) disease prevention at older ages, while valuable to society, holds relatively little promise for saving money, with the notable exception of obesity interventions; and (3) it is health rather than age that drives spending profiles, and a few sentinel conditions are suitable to capture this variation.

Modeling the consequences of health trends and medical technology. Goldman et al. (2005) compare the impact of health trends versus medical innovation. Recent innovations in biomedicine seem poised to revolutionize medical practice. At the same time, disease and disability are increasing among younger populations. This paper considers how these confluent trends will affect the health status and health care spending of the elderly over the next 30 years. Because healthier individuals live longer, cumulative Medicare spending varies little with a beneficiary's disease and disability status upon entering Medicare. On the other hand, ten of the most promising medical technologies – as identified by biomedical experts — are forecasted to increase spending substantially, at a cost of $9,000 to $1.4 million per life-year. There is thus substantial technological risk in future spending by the elderly, and it is unlikely a "silver bullet" will emerge to both improve health and dramatically reduce medical spending.

Disability and spending. Chernew et al. (2005) used the FEM to forecast the impact of changing disability rates on spending by Medicare beneficiaries, accounting for differential spending trends among the disabled. The latter adjustment is important because the composition of the disabled population—and the intensity of treatment for the disabled—are changing. Among community dwelling elderly, spending growth among the least disabled grew at a faster rate

than among the most disabled, which will offset some of the cost savings associated with declining disability rates. Using estimates of spending trends by disability category, the authors project that the cost savings associated with improved disability rates will not dramatically slow the long run rate of growth in Medicare spending.

Consequences of obesity in the elderly. Obesity is recognized as an important public health problem, and it could have serious consequences for older cohorts. Lakdawalla et al. (2005) used the FEM to estimate lifetime costs, life expectancy, disease, and disability for 70-year olds based on body mass (see also, Michaud et al., 2012). Obese 70 year-olds (body-mass index>30 kg/m2) can expect to live approximately the same length of time (13.9 years) as those of normal weight, but they will accumulate more than $39,000 in additional lifetime health expenditures. Moreover, obese 70-year olds will enjoy fewer disability-free life-years, and experience higher rates of diabetes, hypertension, and heart disease. Medicare will spend about 34% more on an obese individual than on someone with normal weight. While these cost differences are already large, they do not include the nonmonetary impacts of obesity, in terms of disability and poor health.

Technological advances in cancer. Bhattacharya et al (2005) used the FEM to examine the consequences for total Medicare expenditures between 2005 and 2030 of scientific progress in cancer. Because technological advance is uncertain, widely varying scenarios are modeled. A baseline scenario assumes year 2000 technology stays frozen. A second scenario incorporates recent cancer treatment advances and its attendant discomfort. Optimistic scenarios analyzed include the discovery of an inexpensive cure, a vaccine which prevents cancer, and vastly improved screening techniques.   Applying the Future Elderly Model, the authors find that no scenario holds significant promise for guaranteeing the future financial health of Medicare.

Lifetime burden of chronic disease among the elderly. The high costs of treating chronic diseases suggest that reducing their prevalence would dramatically improve Medicare's financial stability. Joyce et al. (2005) use the FEM to examine the impact of selected chronic diseases on the distribution of health care expenditures and the variation in spending over the course of disease. They find that a 65-year-old with a serious chronic illness spends $1,000 to $2,000 more per year in health care services than a similar adult without the condition. However,

cumulative Medicare payments are only modestly higher for the chronically ill due to their shorter life expectancy. While reducing the prevalence of chronic disease at age 65 is a worthy goal, it will have only modest effects on Medicare spending.

Age versus Life Expectancy as a Predictor of Health Care Spending. It is unresolved whether age or (expected) remaining life years better predicts health care expenditures. Shang and Goldman (2008) used the FEM to predict life expectancy, and then used regression analyses to compare the predictive power of the two variables in explaining health care expenditures. Age has little additional predictive power on health care expenditures after controlling for life expectancy, but the predictive power of life expectancy itself diminishes as health status measures are introduced into the model. Using life expectancy rather than age results in lower projections of future health care expenditures, suggesting that increases in longevity might be less costly than models based on the current age profile of spending would predict.

5.0   Results

We present the results of the simulations in a series of graphs that depicts the predictions of the FEM between 2005 and 2060. In each graph, we plot three different scenarios which make alternate assumptions about future mortality rates in the population. In the first scenario, depicted as a dotted line in each graph, we assume that mortality rates for every single disease will decline at a rate equal to the decline assumed in the SSA intermediate mortality adjustment scenario. In the second scenario, depicted in the graphs using a dashed line, we assume that mortality rates (conditional on having a disease) will remain fixed at 2005 levels. This scenario thus isolates the effect of changes in the population prevalence of disease on the outcomes of the model. Finally, the third scenario is the same as the first, except that we do not apply the mortality rate improvement adjustment to that the new entrants into the model (who are 51-52 years old each year). After this population ages into the model, however, the assumed improvement in conditional mortality probabilities as the first scenario applies to them. This scenario thus isolates how trends in the health status of younger populations affects the different outcomes that we study. All of the dollar figures in our estimates are inflation adjusted and presented in 2012 dollars.

Figure 2 shows the population size estimates produced by the FEM, while Figure 3 shows forecasted changes in future population mortality rates. Given the structure of the FEM, these estimates are representative of the entire population of the US above the age of 51. By construction, annual mortality rates are substantially higher under the assumption that there will be no future secular improvements in life expectancy. Nevertheless, there are movements in future overall mortality rates that are driven by changes in the health status and age distribution of the future elderly population. Until about 2025, the FEM forecasts reductions in overall mortality, which is consistent with evidence that the health status of older Americans is improving. After that point, however, a right shift in the age structure of the older population will skew the overall mortality rate upward. Despite this increase in the mortality rate, the population size will continue to rise sharply over the entire period from 2005 to 2060.

Figures 4, 5, 6, and 7 demonstrate the change in the age structure of the population under our alternate mortality rate assumptions. In all of our simulations, we find sharp declines in the proportion of the population between the ages of 55-64 starting in about 2020, and reaching its nadir in 2030. Perhaps not surprisingly, the 65-74 year old population reaches its peak in about 2030 and then declines until 2040. The oldest-old population (age 85+) is a roughly constant fraction of the population until about 2030, and then it rises sharply – nearly doubling – until 2050. This population, should it materialize, will pose a sharp burden on Social Security OASI payments, but the existence of the population depends critically on the improvements in survival rates. Figure 7 shows that if survival rates stay at 2005 levels (that is, no mortality adjustments), then the rise in the 85+ population will be substantially less steep and will reach a peak at about 8% of the population in 2050, rather than 12% under the SSA Intermediate Mortality Adjustment Scenario.

Figures 8 through 13 show predicted health status trends in the population under alternative mortality improvement scenarios. The Figures plot prevalence rate trends in the 51+ population in diabetes, hypertension, chronic obstructive pulmonary disease (COPD), stroke, heart disease, and cancer. In every run of the model and for every condition we forecast – with the exception of COPD prevalence – the FEM predicts a sharp increase in prevalence. COPD rates, which are directly related to prior smoking rates, decline in some scenarios, reflecting the

decrease in smoking rates in the population. Recall that the FEM accounts for the competing risks problem in these calculations, so that a decline in mortality from one condition will tend to increase the prevalence rates of all the other conditions. Given this feature of the FEM model, it is perhaps not surprising that if mortality rates are assumed to decline in the population, the predicted prevalence rates of all the health conditions depicted in these figures increase.

Figures 14 and 15 depict predictions in the proportion of the 51+ population claiming OASI benefits and the total amount of predicted OASI payments (in billions of dollars) over the forecast period. The model forecasts a *decline* in the proportion of 51+ year olds claiming until about 2015, followed by a sharp increase in the proportion that continues through 2030. Despite the decline in the proportion of the population claiming benefits, OASI obligations steadily increase up to a level of $2 trillion in annual outlays in 2060. The effect of the various mortality assumption is exactly in accordance with expectations. Under the assumption that there is no secular life expectancy rise, OASI payments do not increase by as much, topping out at $1.75 trillion in annual outlays in 2060. The other two scenarios yield almost exactly the same predictions; apparently, secular mortality trends in the under 51 year old population are not as important as secular trends in mortality in the over 51 population. Figure 15 serves also a check on the validity of the FEM model since it is based on data from prior to 2006; using these data, the FEM predicted that OASI expenditures would be $625 billion in 2012. This is close to (though a slight underestimate of) the actual 2012 OASI payments of $637.

Figures 16 and 17 show the FEM predictions in the proportion of the population 51+ claiming Supplemental Security Income (SSI) benefits and total SSI payments (in billions of dollars). Unlike OASI participation, the FEM predicts a sharp rise in SSI participation (up to about 3% of the 51+ population) over the next few years and a plateau at that level through 2060. SSI payment levels in this population are an order of magnitude less than OASI payments. The FEM predicts a steady increase in SSI obligations until 2060, topping out at about $50 billion. There is one important caveat, though, in interpreting this figure – the FEM only predicts expenditures on the 51+ population. Since a large portion of SSI payments goes to the under-50 population, the FEM only forecasts a portion of what the ultimate outlays will be.

Finally, Figures 18 and 19 show predicted trends in the proportion of the age 51+ population claiming Social Security Disability Insurance (DI) benefits, as well as total DI payments (in billions of dollars). For this population, the FEM predicts a *decline* in the proportion claiming benefits from about 4% of the population down to about 3% of the population until about 2030, and then a plateau. Despite this decline, the model forecasts a sharp increase in DI outlays between 2006 and 2020 from about $40 billion annually to about $60 billion, followed by a plateau at $60 billion until 2030, and then another sharp rise to nearly $100 billion in annual expenditures by 2060. As is the case with the FEM SSI forecasts, this represents only a portion of DI obligations since it focuses on the 51+ population, and there are many under 51 who qualify for DI benefits. Also, it is well known that DI payments fluctuate closely with changes in the unemployment rate (Autor and Duggan, 2006). The FEM is not designed to capture these business cycle fluctuations, and instead yields a smooth prediction that reflects health and demographic trends.

6.0   Discussion

The Future Elderly Model is a detailed microsimulation model of the health of the future American population that enables researchers and policy makers to obtain projections of future government obligations on Social Security, including on OASI, SSI, and DI expenditures for the age 51+ population. All three of these expenditure outcomes will depend critically on the future health of the population since life expectancy is a key input into Social Security expenditures. However, health status trends over the past thirty years paint a complicated picture; in some ways Americans have become more healthy – for instance, arthritis rates have declined – while in others Americans have become less healthy. Obesity prevalence and concomitant chronic diseases like diabetes have become substantially more common. A detailed model such as the FEM is necessary to account for these conflicting trends in a way that also addresses the competing risks problem.

In addition, it is increasingly common for the elderly to have multiple chronic conditions. This is especially important because multiple chronic diseases act synergistically on probability of

death, with predictable effects on life expectancy. Existing Social Security forecasting models tend to ignore the possibility of coexisting chronic conditions. For instance, Social Security Office of the Actuary's (OACT) forecasting models account for cause-specific mortality from a small number of singleton conditions, and do not consider multiple conditions at all. The FEM uses the best available evidence from large nationally representative longitudinal surveys of health to account for these interactions.

In this paper, we use the FEM to address a key question that all Social Security forecasting models must address – how do different assumptions about secular trends in mortality conditional on health status affect forecasted Social Security participation and expenditures? While some have argued that Social Security underestimates future reductions in conditional mortality (Soneji and King, 2012), in this paper, we estimate a baseline model that is consistent with the OACT model's intermediate assumptions about mortality reductions.

In addition, we forecast two additional scenarios. In one, we assume no future changes and conditional mortality. Thus, in this scenario, only changes in the future prevalence of chronic disease drive Social Security expenditure changes. In the third scenario, we assume that conditional mortality reductions will only apply to people above 52 years of age, and that there will be no improvements in conditional mortality for younger incoming cohorts. This is an important scenario because it allows us to explore the relative importance of investments in mortality rate reductions among younger populations on Social Security expenditures.

Our main findings are as follows:

- Due to changes in the health status of the American population alone, mortality rates will decline in the 51+ population until about 2025, and then will rise sharply until about 2050.

- Under all our scenarios, the size of the American 51+ population will increase steadily throughout the coming decades, reaching a total of between 145 and 160 million people (depending on the assumptions about reductions in conditional mortality rates).

- The age structure of the 51+ population will shift dramatically toward older ages, with the size of the 85+ population in particular experiencing the sharpest growth.

- Under all of our scenarios, diabetes, hypertension, stroke, heart disease and cancer prevalence will increase (in many cases sharply) in the age 51+ population throughout the coming decades. These forecasted prevalence rates are not sensitive to assumptions about future changes in conditional mortality rates.

- The proportion of the age 51+ population claiming OASI will increase sharply in the coming decades, reaching a plateau in 2030; OASI expenditures, by contrast, will increase steadily through 2060, reaching between $1.5 trillion and $2 trillion in annual payouts (depending on conditional mortality rate assumptions).

- The proportion the age 51+ population claiming SSI will increase sharply until 2020, and then reach a plateau through 2060. As with OASI payments, SSI payments will increase steadily through 2060, reaching a level of about $50 billion per year for the 51+ population.

- Finally, DI participation rates will fall sharply through 2030 and then plateau. Despite this fall, DI expenditures will rise to nearly $100 billion in expenditures for the 51+ population by 2060.

Our finding reinforce the well-accepted sense among demographers that the upcoming decades of the 21st century will impose a steep burden on the federal government to finance Social Security. The FEM highlights the role that the future health of the population will play in a transparent way. Our main, dispiriting, finding is that whether or not medical technology improves or stagnates in its ability to keep chronically ill patients alive, the worsening health of the future elderly population, combined with presently low conditional mortality rates will combine to make the financial position of Social Security worse over the coming decades.

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APPENDIX: Detailed Description of the Future Elderly Model

The future elderly model (FEM) is a demographic-economic microsimulation to project future health and medical spending among the elderly. At its core is a detailed model of chronic disease incidence and prevalence that is matched to nationally representative data on mortality and morbidity and a closely matched health expenditure model. The model differs from other approaches in that it includes a multi-dimensional characterization of health status. Conventional actuarial approaches employ cell-based models in which each cell represents a subpopulation of interest. To capture the heterogeneity of the elderly population (health status, sex, age, race, and so on), the number of cells would need to be very large and cell sizes would be correspondingly small. Microsimulation models offer a conceptually and analytically superior alternative.

A.1 Model Overview

Microsimulation models start out a large sample of simulated individuals. Each individual is characterized by a state vector, which in our case includes an array of health status indicators. For expositional purposes, suppose indicators for A (say, peptic ulcer), B (say, arthritis), and C (say, stroke) constitute the state vector. The health states are obviously not mutually exclusive and they may or may not be "absorbing," (that is, it is possible to recover from some conditions).   Let H be the "healthy" state in which the person is free from A, B, and C, and D the "deceased" state. Individuals may then be H; A; B; C; A+B; A+C; B+C; A+B+C; or D. Initially, and for each simulated individual, we randomly assign a health state. For this purpose, we need prevalence estimates of each possible combination of health states from a large nationally representative dataset. The random assignment is done so that the prevalence rates of all the states (H; A; B; C; A+B; A+C; B+C; A+B+C) match those in the nationally representative dataset.

Next, we map out individuals' remaining life paths and identify at what point(s) in time they transition into other health statuses, and when they die. To do this, we estimate transition models into all possible health states. In the example, we need four models: transition into A, into B, into C, into D(deceased), plus additional recovery models. This approach requires us to assume independence in disease incidence (conditional on covariates) unless we specifically

define a separate health state as a combination of A+B, for instance. We estimate these health transition models using standard discrete dependent variable methods using a nationally representative longitudinal dataset. Such models may account for health history in a flexible way. If the models only account for current information, a first-order Markovian process is generated; if they account for lagged covariates, such as accumulated health histories, higher-order Markovian processes result. Transition models may be estimated using any data source that contains health measures that are identical to those distinguished in the microsimulation sample. In the most detailed version of the model, we estimate a different health transition model for each combination of fixed covariates (sex and race, for instance). Finally, we project future health transitions for each simulated individual using the health transition models. The result is a simulated life path in which the person accumulates multiple disease conditions, and then dies.

The cost model is an empirically derived mapping from the health state vector and the vector of demographic variables (such as age, race, and sex) to health care expenditures assuming a static medical technology. In the original FEM, this mapping is constructed using the Medicare Current Beneficiary Survey (MCBS), which is a nationally representative sample of Medicare beneficiaries in the U.S. With this mapping we calculate, for each simulated individual in each year, expected Medicare expenditures as well as other outcomes of interest, such as out-of-pocket health expenditures, and inpatient and outpatient expenditures. This is simple because the covariates included in the cost model are exactly the same as those included in the health state vector.

Finally, we need a rejuvenation model that forecasts the health status of incoming cohorts of 65 year olds, which is the first age at which people qualify for Medicare (unless they are severely disabled). The FEM rejuvenation model relies on a synthetic cohort approach to forecasting the health of future cohorts of 65 year olds. We draw introduce new 65 year old simulated individuals with health and demographic status determined by the rejuvenation model.

Figure 1 depicts how the cost models, transition models, and rejuvenation models are integrated into our microsimulation model. The model is designed to yield predictions in constant dollars and—at baseline—using medical technology fixed at a given year. We start with MCBS data for 2000 as the host cohort. The characteristics of these individuals are used to predict per capita 2000 medical expenditures. The weights of the host data are adjusted such that they add up to the 2000 population of individuals age 65 and older. The product of per capita expenditures and population size yields aggregate 2000 medical expenditures. The host data include some individuals who, at the time of their last interview of their first year in the MCBS had become deceased. These are dropped from the sample. We then project individuals' health status in 2001. By then, the sample has aged to 66 years of age and older. We rejuvenate the sample using the sample of 65-year old MCBS respondents. The weights of newly entering individuals are adjusted, first, in accordance with 2001 prevalence rates of health conditions among 65-year olds, and second, such that the sum of weights for age 65 in the simulation sample equals the 2001 population of individuals age 65. The resulting sample is representative of the 2001 age 65+ population. We use the health status and demographic characteristics of this sample to predict per capita medical expenditures and derive the aggregate expenditures in 2001. We then repeat this process iteratively for as many years as our forecast requires.

A.2   Modeling Health

Health measures must meet several competing goals. First, they should predict costs. Second, they should capture clinically relevant disease. Third, they should be readily available in the data available to us. The FEM model defines health states based on both self-reported health conditions, as well as on health states derived from Medicare claims data. The MCBS asks about a multiplicity of health conditions. We focus on conditions that are most prevalent in the elderly population and also the most expensive to treat. The conditions we use include cancer (breast, prostate, uterine, colon, bladder, lung, kidney, throat, and brain); heart disease (angina or myocardial infraction); stroke; diabetes; hypertension; lung disease; and arthritis. We also include body mass index (BMI), indicators for the presence of activity of daily living limitations, and whether each individual ever smoked among the health state variables. The limitation of

this approach is that the sample sizes in the MCBS prevent us from considering many jointly occurring conditions (A + B, for instance). This is most problematic for several conditions that act synergistically in generating health expenditures (diabetes, hypertension, and heart disease, for instance).

A.2.1   Health Transitions

For conditions such as cancer, diabetes, and hypertension, the MCBS questions were worded as "Did a doctor ever tell you that …" Thus, having a condition is a permanent (absorbing) state. Accordingly, we only model transitions into these states with no chance for recovery. In current version of the FEM, we model transitions into mortality, cancer, cardiovascular disease, diabetes, hypertension, and facility residence with a proportional hazard models:

$$\ln h_j(t) = \gamma' Age(t) + \beta X_j$$

Here $\ln h_j(t)$ is the log-hazard of onset of the jth condition (including mortality and entry into a facility); $Age(t)$ is a piecewise-linear spline transformation of age at time t; and X_j are demographic characteristics and co-morbidities that affect the onset of condition j. The baseline duration dependency is the dependency on respondent age, $\gamma' Age(t)$. The hazards of various conditions' onset are assumed to be linear in age, with potentially different slopes before and after age 77.

The unit of observation is an interview-pair. All explanatory covariates are measured with a one-year lag. Only individuals who, at the time of the first interview, did not suffer from a specific condition contribute to the model estimation. For example, consider an individual who entered the MCBS in 1993 without cancer but with a heart condition. In 1994, his conditions are unchanged; in 1995, he is diagnosed with cancer; in 1996, his conditions are unchanged. This person starts out with a heart condition, so he does not at all contribute to the heart disease transition model. In 1993 and 1994, he is free of cancer, so he contributes two observations to the cancer transition model. The outcome in his first contribution (1993 to 1994) is zero, because he remained free of cancer; the outcome in his second contribution

(1994 to 1995) is one, because he was diagnosed with cancer. He is out of the sample for subsequent years.

Table 1 presents the estimation results for hazard models of onset of cancer, heart disease, stroke, arthritis, Alzheimer's, lung, hypertension, and diabetes. The coefficients on age indicate the baseline slopes on age. They are generally positive, i.e., the risks of onset of various conditions tend to increase with age. It may surprise that the age coefficients tend to be smaller after age 77 than before, i.e., that there is a deceleration in the risk pattern. Note, however, that this age pattern applies only to individuals without any co-morbidity. As individuals get older, they are more likely to suffer from various conditions, which have positive effects on the onset of other conditions. The net result is typically an acceleration of the log-hazard with age. We return to this issue below, in the discussion of mortality. Positive coefficients in Table 1 indicate a higher hazard and thus poorer health. The coefficients indicate shifts in the log-hazard and thus proportional shifts in the hazard or risk of onset. For example, hypertension increases the log-hazard of heart disease by 0.47, i.e., it increases the risk of heart disease by 100*(exp(0.47)-1)≈60 percent.

Table 2 shows selected estimates of the hazard model of *mortality*. The first and second columns show log-hazard coefficients; the third shows percent changes in the mortality risk. These estimates are based on MCBS data. The MCBS may or may not capture all deaths, so the next subsection compares MCBS estimates to Vital Statistics. As before, all explanatory covariates are measured with a one-year lag, i.e., as of the first interview of the interview-pair. Most health conditions increase the risk of mortality.

A.2.2   Unobserved Heterogeneity and Left-Censoring

The presence of persistent unobserved heterogeneity (frailty) could contaminate the estimation of dynamic pathways or "feedback effects" across diseases. In addition, many health conditions are left-censored—that is, respondents enter the study with a health condition or functional status limitation already present. We have estimated a version of the FEM that adjusts for these factors using the Health and Retirement Study. Since we have a stock sample

from the age 50+ population, each respondent goes through an individual-specific series of intervals. Hence, we have an unbalanced panel over the age range starting from 50 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 incidence at ages $j_i = j_{i0} \dots j_{iT_i}$.

Record as $h_{i,j,m} = 1$ if the individual has condition m 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 disease m, $\eta_{i,m}$. The time-varying part is the effect of previously diagnosed health conditions $h_{i,j_i-1,\sim m}$, (other than the condition m) on the hazard.[2] We assume an index of the form $z_{m,j_i} = x_i\beta_m + h_{i,j_i-1,\sim m}\gamma_m + \eta_{i,m}$. Hence, the latent component of the hazard is modeled as

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

$$\text{for } m = 1 \dots M, j_i = j_{i0} \dots j_{iT_i}, i = 1 \dots N$$

We approximate a_{m,j_i} with an age spline. Diagnosis, conditional on being alive, is defined as

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

$$\text{for } m = 1 \dots M, j_i = j_{i0} \dots j_{iT_i}, i = 1 \dots N$$

We consider 7 health conditions to which we add functional limitations (disability) and mortality. Each of these conditions is an absorbing state. The same assumption is made for ADL limitations, the measure of disability we use. The occurrence of mortality censors observation of diagnosis for other diseases in a current year. The term $\varepsilon_{i,j_i,m}$ is a time-varying shock specific to age j_i. We assume that this last shock is Type-1 extreme value distributed, and uncorrelated across diseases.[3] Unobserved difference $\eta_{i,m}$ are persistent over time and are allowed to be correlated across diseases $m = 1 \dots M$. However, to reduce the dimensionality of the heterogeneity distribution for computational reasons, we consider a nested specification. We assume that heterogeneity is perfectly correlated within nests of conditions but imperfectly

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[2] With some abuse of notation, $j_i - 1$ denotes the previous age at which the respondent was observed.
[3] The extreme value assumption is analogous to the proportional hazard assumption in continuous time.

correlated across nests. In particular, we assume that each of first 7 health conditions (heart disease, hypertension, stroke, lung disease, diabetes, cancer and mental illness) have a one-factor term $\eta_{i,m} = \tau_m \alpha_{iC}$ where τ_m is a disease specific factor-loading for the common individual term α_{iC}. We assume disability and mortality have their own specific heterogeneity term α_{iD} and α_{iM}. Together, we assume that the triplet $(\alpha_{iC}, \alpha_{iD}, \alpha_{iM})$ has some joint distribution that we will estimate. Hence, this vector is assumed imperfectly correlated. We use a discrete mass-point distribution with 2 points of support for each dimension (Heckman and Singer, 1984). This leads to $K = 8$ potential combinations.

The parameters $\theta_i = (\{\beta_m, \gamma_m, \mu_m, \tau_m\}_{m=1}^M, F_\alpha)$ can be estimated using maximum likelihood, where F_α are the parameters of the discrete distribution. Given the extreme value distribution assumption on the time-varying unobservable (a consequence of the proportional hazard assumption), the joint probability of all time-intervals until failure, right-censoring or death conditional on the individual frailty is the product of Type-1 extreme value 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 $\alpha_i = (\alpha_{iC}, \alpha_{iD}, \alpha_{iM})$ 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)

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

We make explicit the conditioning on $h_{i,j_{i0}} = \left(h_{i,j_{i0},0}, \dots, h_{i,j_{i0},M} \right)'$, we have no information on health 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 $h_{i,j_{i0},\sim m}$, the initial condition 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 $p(\alpha_i | h_{i,j_{i0},0})$. Implementing this solution amounts to including initial

prevalence of each condition at baseline each hazard. Therefore, this allows for permanent differences in the probability of a diagnosis based on baseline diagnosis on top of additional effects of diagnosis on the subsequent probability of a diagnosis. The likelihood contribution for one respondent's sequence is therefore given by $l_i(\theta; h_{i,j_{i0}}) = \sum_k p_k l_i(\theta; \alpha_i, h_{i,j_{i0}})$, where the p_k are probabilities for points of support α_k, $k = 1 \dots K$.

We have estimated this version of the FEM using the BFGS algorithm and found that it fits the data quite well (and that it fits the data better than a model that does not control for initial conditions). For example, we have estimated the model using half of the sample, and then simulated outcomes for the 1992 HRS respondents who were not included in the estimation sample. We then compared simulated outcomes 12 years later (2004) with the actual outcomes, as shown in Table 3. In general, the model fits the data quite well, with a close correspondence between predicted and actual outcomes for functional status and disease.

A.3. Modeling Expenditures

To project medical costs (not shown in this paper), we use longitudinal data from the Medicare Current Beneficiary Survey (MCBS) Cost and Use files. Reimbursements in the MCBS are categorized into nine different service groups, such as inpatient care, ambulatory services, outpatient prescription drugs, home health, and institutional care. This level of cost detail allows us to explore how new therapies and technologies affect treatment and outcomes and how the mix of services change over time and across patient subgroups.

The cost analyses exclude enrollees under age 65 and persons enrolled in HMOs. These exclusions yield an average yearly sample of about 8,600 beneficiaries. All the costs are adjusted by medical CPI and measured in 1998 dollars. Average Medicare expenditures increased 11.5 percent in real terms between 1992 and 1998, reflecting increased per capita utilization. The number of enrollees in our sample declined over time, primarily due to increased HMO enrollment and greater numbers of younger beneficiaries who were excluded from the analyses.

We impute costs in the microsimulation by computing fitted values from cost regressions. The primary dependent variables used in the cost regressions are Medicare reimbursements and

their components (Part A and Part B reimbursements), and total medical expenses.4 The set of independent variables include demographics such as age, gender, ethnicity, education, and geography (region and urban residence), death, as well as the health state variables. We apply similar methods to estimating Social Security expenditures – OASI, SSI, and DI – payments, however, because these expenditures are not available in MCBS data, we rely on the Health and Retirement Study (HRS) data instead.   We estimate regression models for each of the Social Security expenditure and participation probability outcomes using the same set of explanatory variables that we use in the Medicare expenditure analysis.

A.4   Modeling the Incoming Cohort (51 year-olds)

Our strategy to predict the health status of future cohorts of incoming 51 year-olds proceeds in four stages. First, for each chronic disease condition of interest, we use the National Health Interview Survey (NHIS) data to obtain age-specific prevalence information. Though the NHIS has a large sample size overall, for some age-cohorts the sample size is insufficient to produce noise-free estimates of low prevalence diseases. Thus, we introduce a method to smooth the NHIS age-specific prevalence profiles, while at the same time accounting for trends in disease prevalence. Second, we use a synthetic cohort-based procedure to obtain age-specific incidence rates from the smoothed prevalence profiles. In particular, we compare the prevalence of a disease in one year for one age-cohort with the prevalence rate of that disease in the next year of data (where that cohort has aged by one year). Our procedure adjusts these raw prevalence differences to account for population and disease-specific death rates. Third, we combine information from the most recent NHIS with our estimated age-specific incidence rates to obtain our predictions about the health status of the future incoming Medicare cohorts. For example, we add the prevalence of disease among 50 year olds in 2005 to our estimated incidence rate for that disease among 50 year olds to obtain our predictions about the 2006 class of 51 year olds. Fourth, we take our estimates of future prevalence among the

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[4] A panel of social science experts recommended not distinguishing the components of costs—e.g., inpatient, outpatient, and home health—because trends during the 1990's were so extreme, and this is the period spanned by our data.

entering cohort and use them to construct adjustments to the population weights of future entering cohorts with the various disease conditions.

In our model, the population transitions between health and illness from year to year. At time t, the size of the population who are aged a is given by $Pop_{t,a}$. The size of the age a diseased population at time t is given by $P_{t,a} < Pop_{t,a}$. The $Pop_{t,a} - P_{t,a}$ patients without the disease condition die from all other causes at a yearly rate given by $\pi_{t,a}$ and they develop the disease condition at the age- and year- specific incidence rate $i_{t,a}$. $P_{t,a}$ patients die from the disease at a yearly rate given by $r_{t,a}$ and are cured at a rate given by $c_{t,a}$.

The transition equation linking the population size of a given cohort from one year to the next is then given by:

(1) $Pop_{t+1,a+1} = Pop_{t,a} - (Pop_{t,a} - P_{t,a})\pi_{t,a} + P_{t,a}r_{t,a}$

Dividing through by $Pop_{t,a}$, we write (1) in terms of the population age-specific prevalence of the disease, $\rho_{t,a}$, and the cohort growth rate $\gamma_{t,a}$:

(2) $\gamma_{t,a} \equiv \frac{Pop_{t+1,a+1}}{Pop_{t,a}} = 1 - (1 - \rho_{t,a})\pi_{t,a} + \rho_{t,a}r_{t,a}$

The number of people with chronic diseases in that cohort at $t + 1$ will equal all of those with the disease in the previous year save those who are cured or died, plus all the health people in the cohort who develop the disease. Therefore, the number of chronically ill within a fixed cohort evolves according to the following equation (after dividing through by $Pop_{t,a}$):

(3) $\gamma_{t,a}\rho_{t+1,a+1} = i_{t,a} + \rho_{t,a}(1 - i_{t,a} - r_{t,a} - c_{t,a})$

Finally, we rearrange (3), solving for $\boldsymbol{i_{t,a}}$ to write the age-incidence curve as a function of successive measurements of disease prevalence:

(4) $\boldsymbol{i_{t,a}} = \frac{\gamma_{t,a}\rho_{t+1,a+1} - \rho_{t,a}(1 - r_{t,a} - c_{t,a})}{1 - \rho_{t,a}}$

We use information from the NHIS to generate estimates of disease prevalence rates, $\rho_{t+1,a+1}$ and $\rho_{t,a}$. We use information from Vital Statistics (2000) to generate information on disease

specific death rates $r_{t,a}$ and on overall death rates $1 - \gamma_{t,a}$. Data on disease specific cure rates are nowhere available from any single consistent source. Consequently, in our calculations we assume that $c_{t,a} \ll r_{t,a}$. Because we are considering only chronic diseases with low cure rates, this assumption should not introduce too much error.

Finally, taking linear combinations over t of $i_{t,a}$ generates age-incidence profiles that are representative for the period over which the linear combination is taken. Thus, in this framework it is easy to incorporate information about trends in disease or disability, at least to the extent that such trend evidence is present in the successive NHIS years that we use. Let the linear combination of age-incidence profile be i_a.

Once the prevalence and incidence functions are calculated for each disease separately, we generate our projections for the health status of future entering cohorts of Medicare enrollees. The essential idea behind our projection is that for any given future year, we know how old the entering Medicare cohort is today. For example, writing in the year 2013, we know that the 51 year olds of 2014 are currently 50 years old; $\rho_{2013,64}$ gives the prevalence of chronic disease among this cohort, and i_{50} gives the predicted proportion of those without disease in that cohort who will develop the disease between ages 50 and 51 (among those who are disease free at 50). The disease prevalence for 51 year olds in 2014 is given by a direct application of equation (3).

$$(5) \qquad \rho_{2014,51} = \frac{1}{\gamma_{2013,50}} \Big(i_{50} + \rho_{2013,50}\big(1 - i_{50} - r_{2013,50}\big) \Big)$$

Recursive application of equation (5) to different cohorts in the NHIS data yields predictions regarding the prevalence of this disease condition for the entering cohort of any future year y (as long as the cohort is alive at the time of the latest NHIS). By starting with progressively younger cohorts, and applying the recursion formula (5) more times, we generate projections of disease prevalence for incoming cohorts for each year between 2014 and 2060. In principle, this method could be used to project disease prevalence for any future year, as long as the group of people who will be 51 in that year are alive today. Finally, by assuming that each disease occurs independently, we project the joint incidence of disease in incoming cohorts as well.

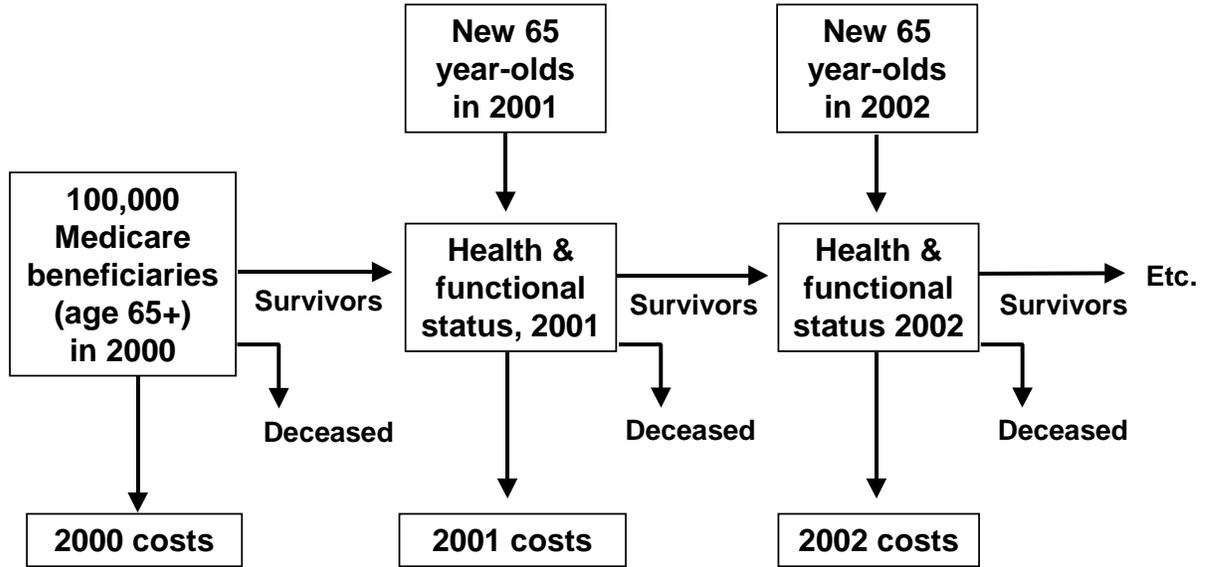**Figure 1. Components of the Future Elderly Model**

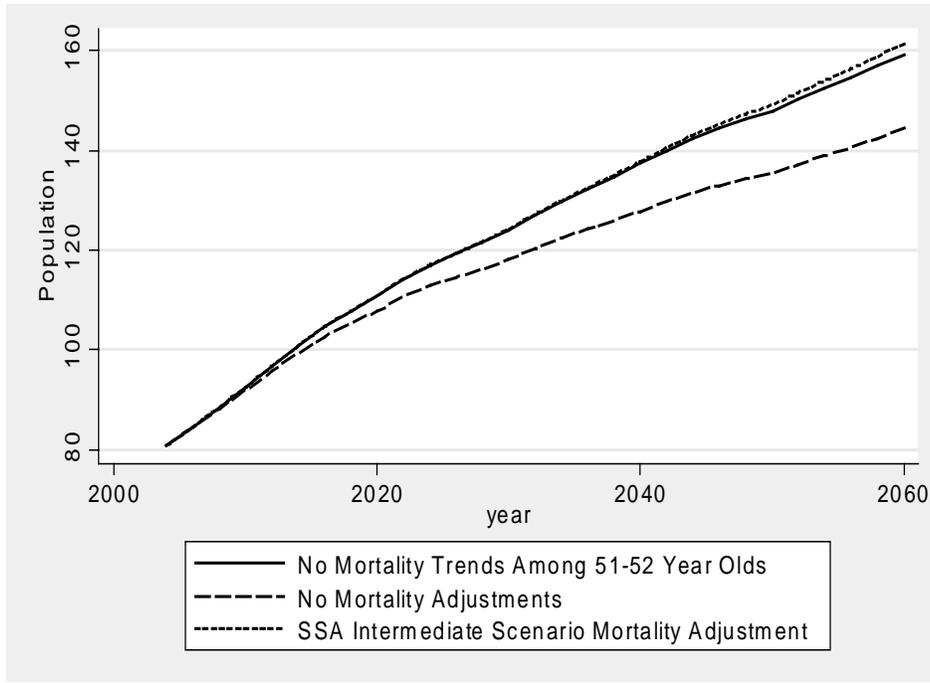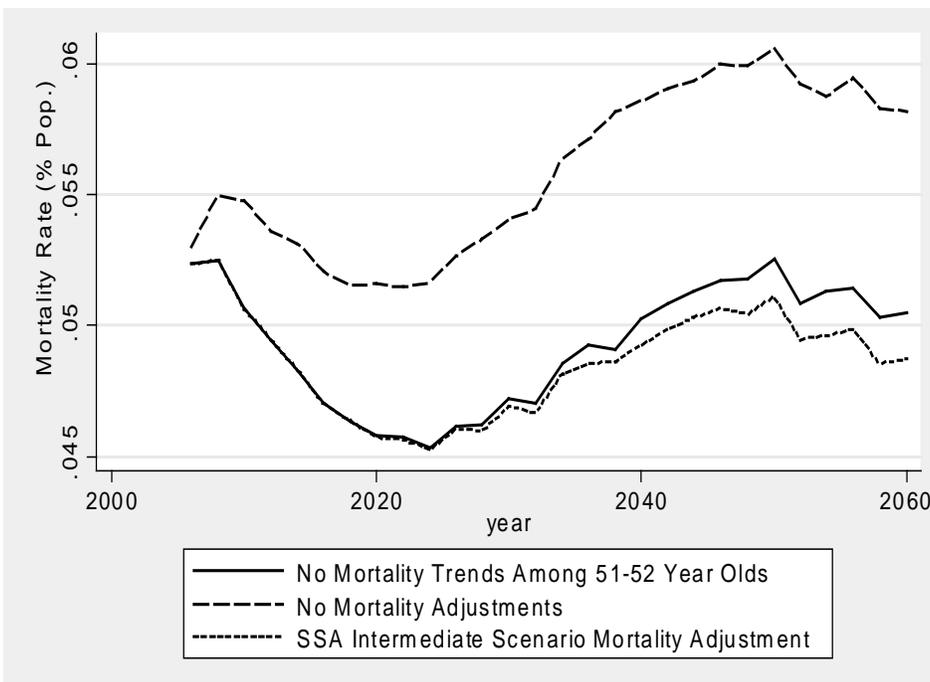**Figure 2: FEM Population Forecasts (Age 51+, US)**

Legend:
- No Mortality Trends Among 51-52 Year Olds
- No Mortality Adjustments
- SSA Intermediate Scenario Mortality Adjustment

Figure 3: FEM Mortality Rate Forecasts

Legend:
- No Mortality Trends Among 51-52 Year Olds
- No Mortality Adjustments
- SSA Intermediate Scenario Mortality Adjustment

Figure 4: FEM Population Forecasts (Age 55-64)
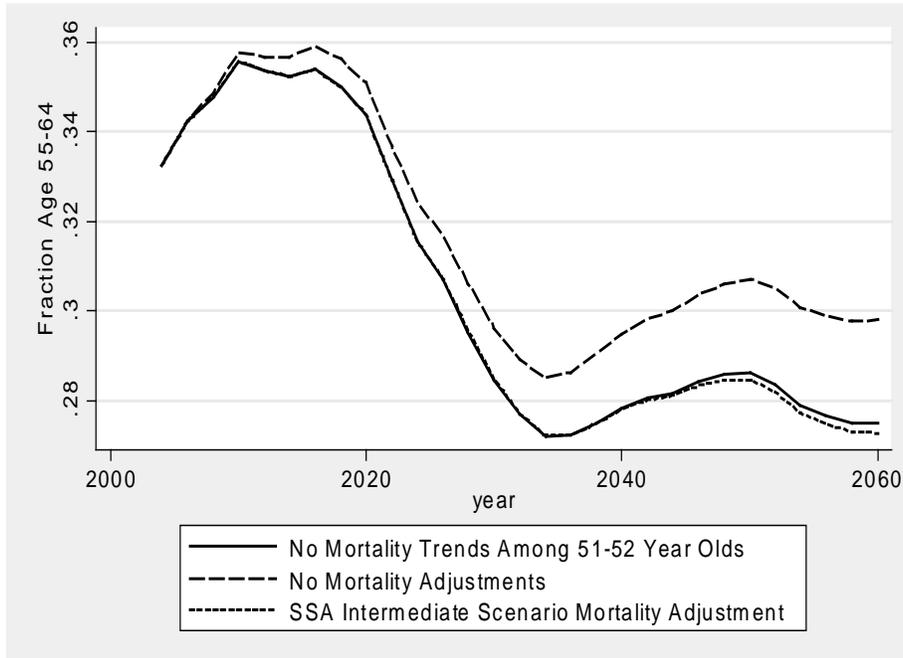
Figure 5: FEM Population Forecasts (Age 65-74)
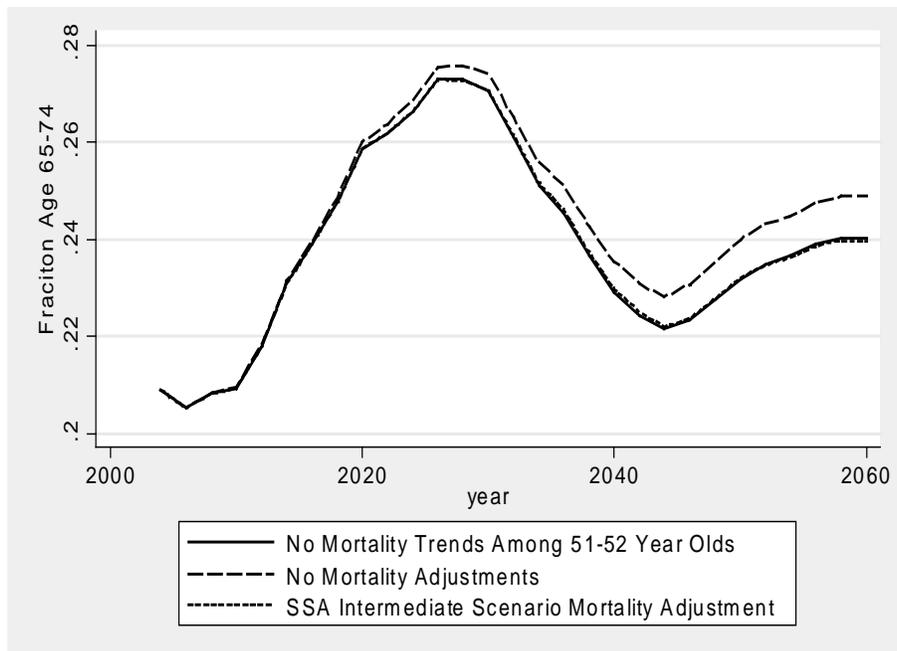
Figure 6: FEM Population Forecasts (Age 75-84)
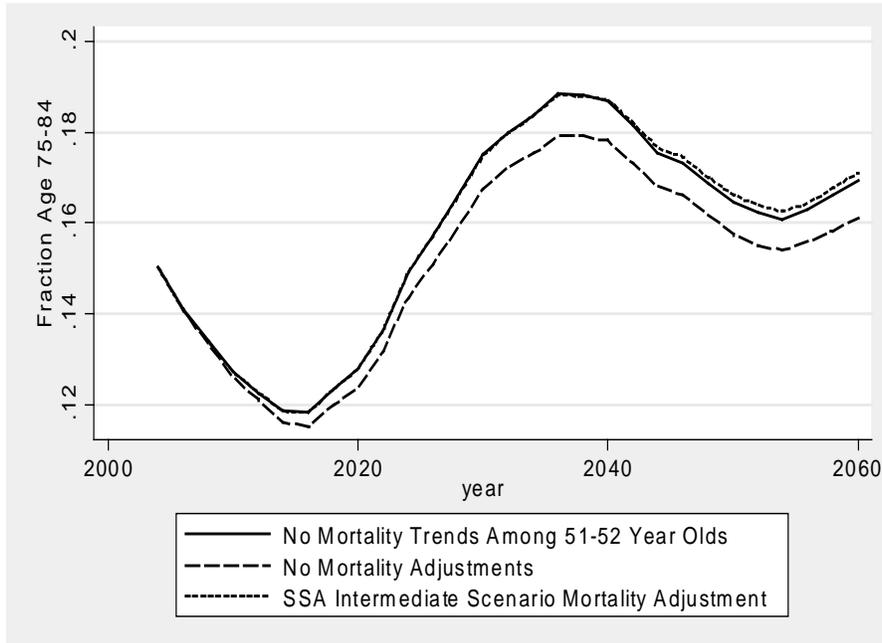
Figure 7: FEM Population Forecasts (Age 85+)
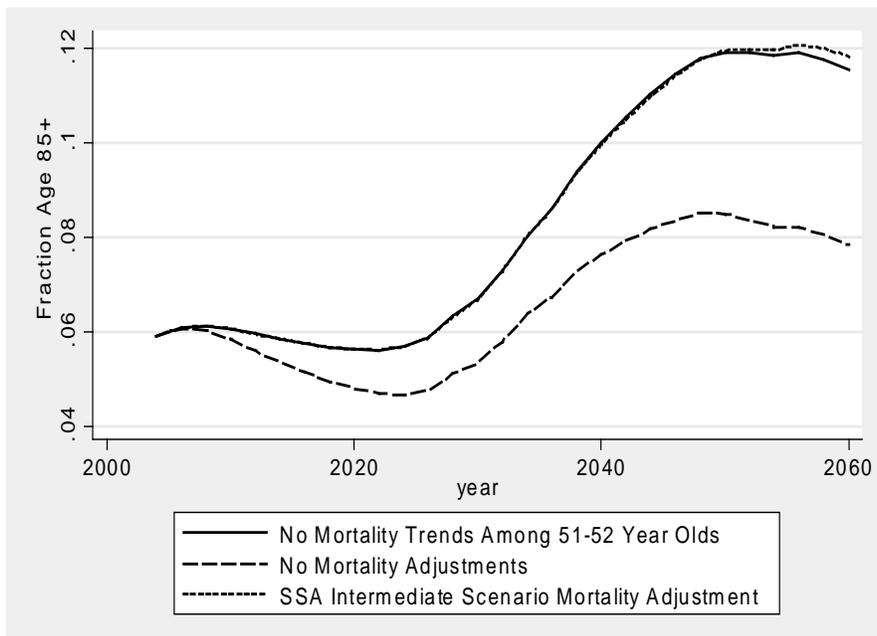
Figure 8: Diabetes Prevalence Forecasts
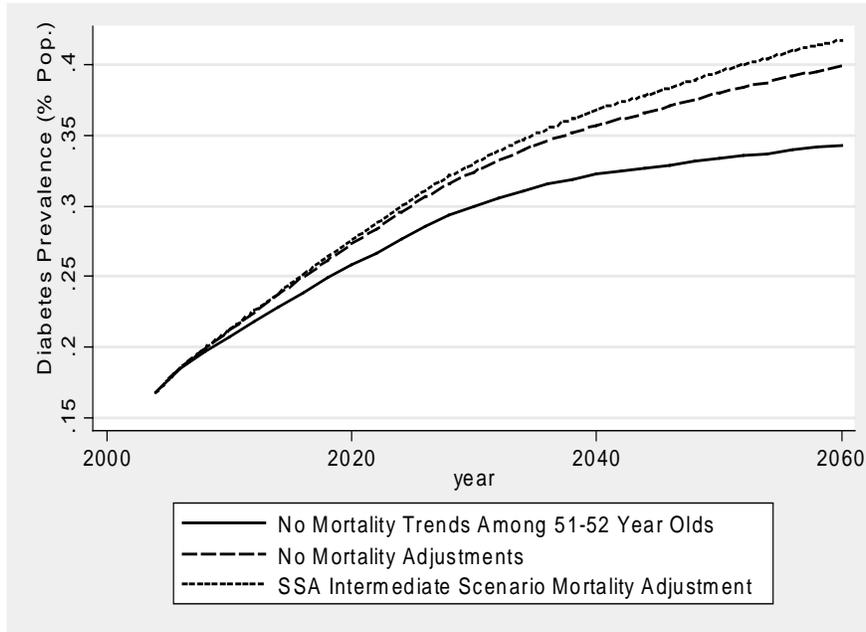
Figure 9: Hypertension Prevalence Forecasts
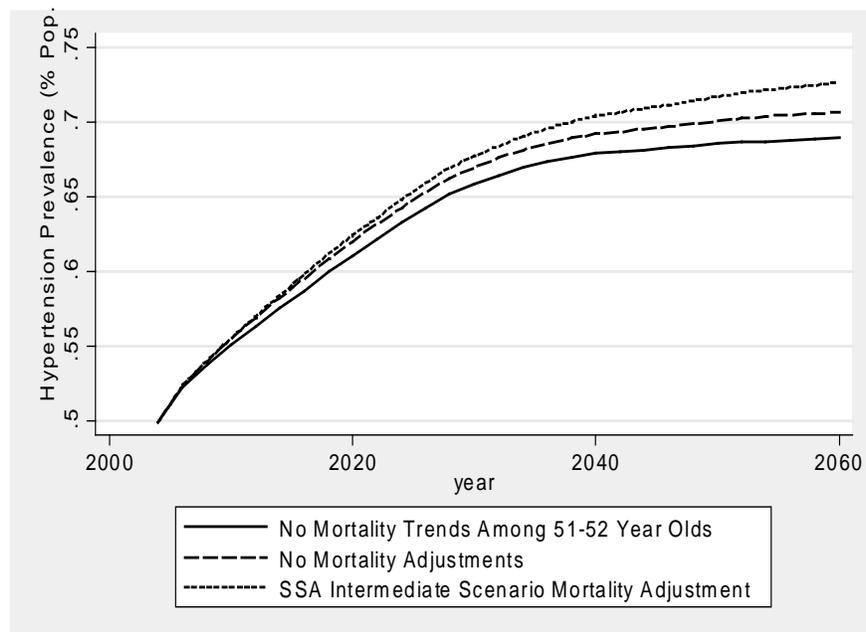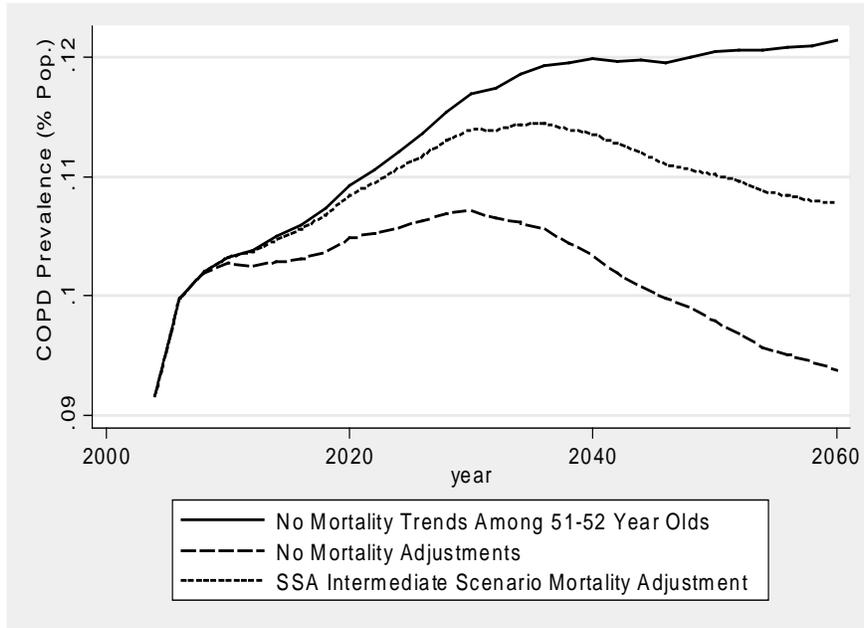
Figure 10: COPD Prevalence Forecasts
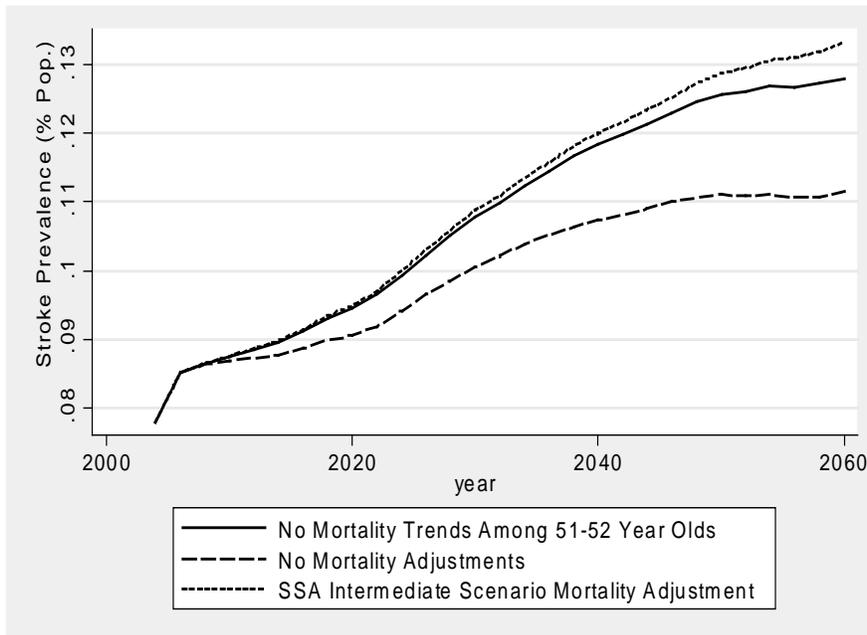

Figure 11: Stroke Prevalence Forecasts

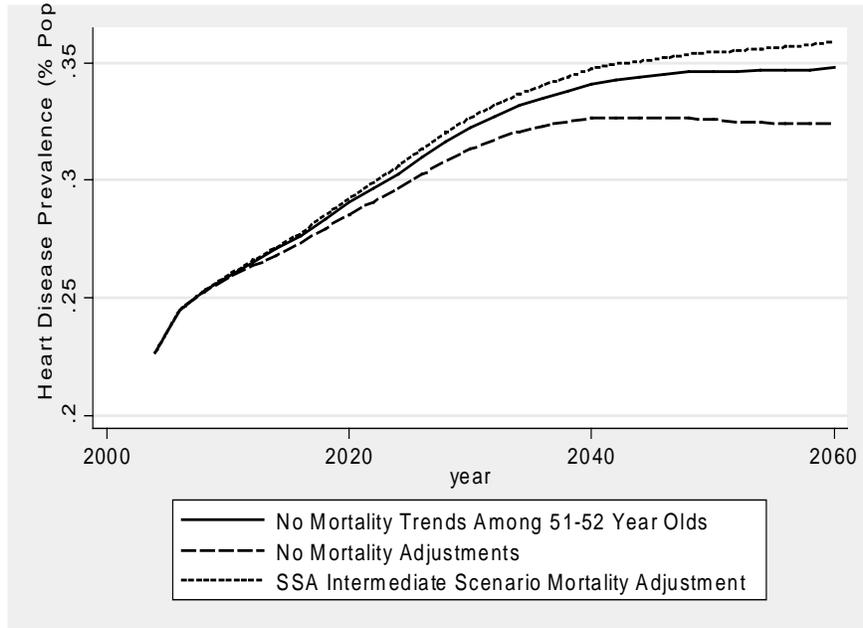**Figure 12: Heart Disease Prevalence Forecasts**

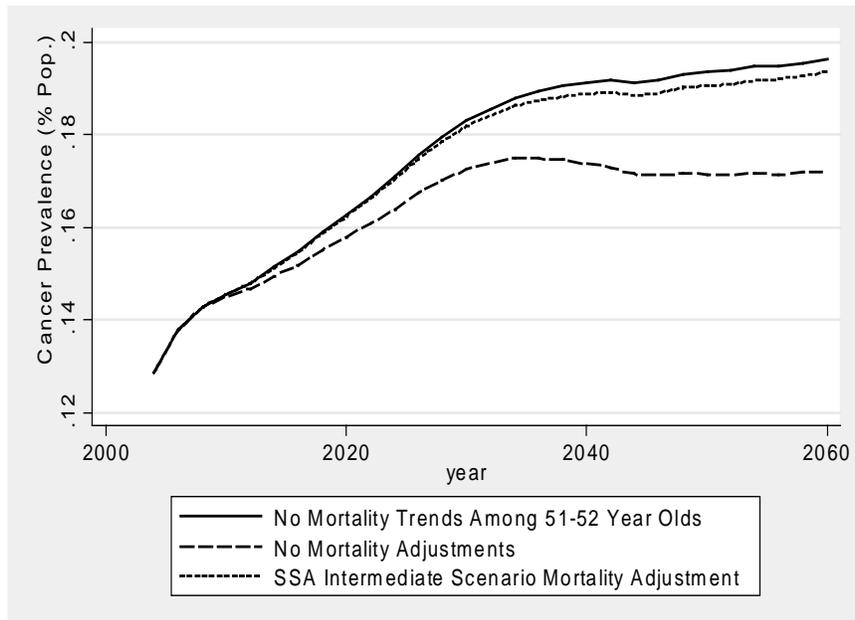**Figure 13: Cancer Prevalence Forecasts**

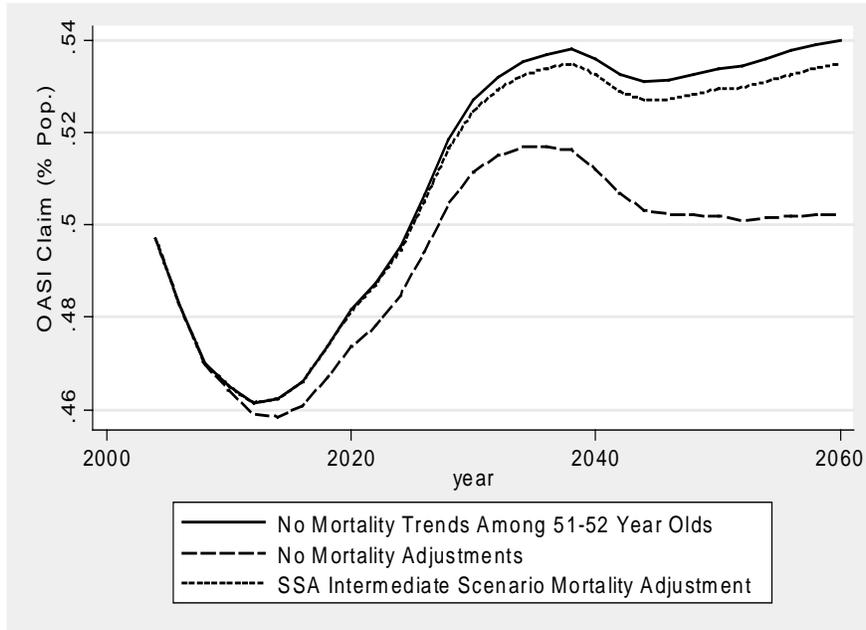**Figure 14: Proportion of Age 51+ Population Claiming OASI**

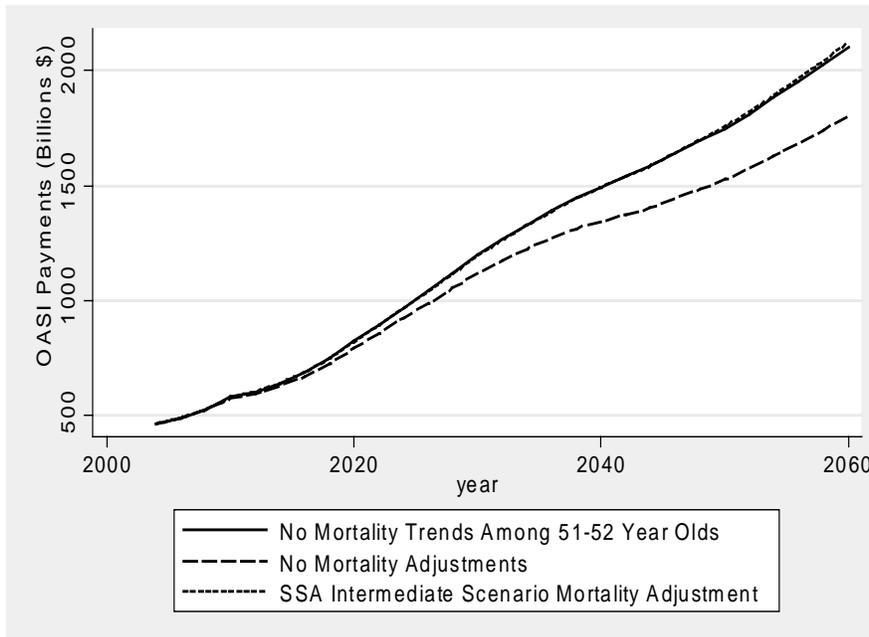**Figure 15: OASI Payment Forecast (for Age 51+ Population)**

Figure 16: Proportion of Age 51+ Population Claiming SSI
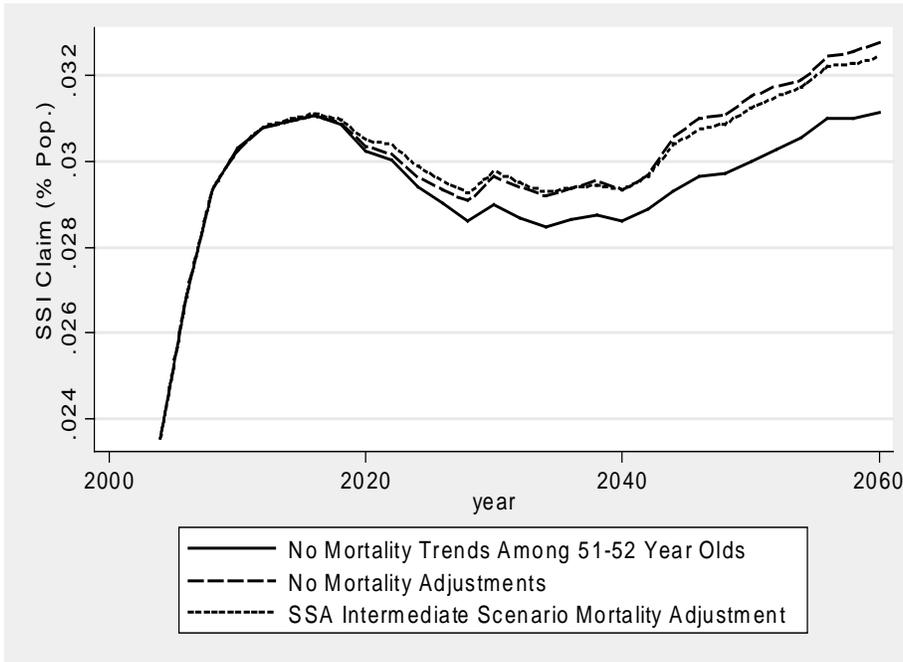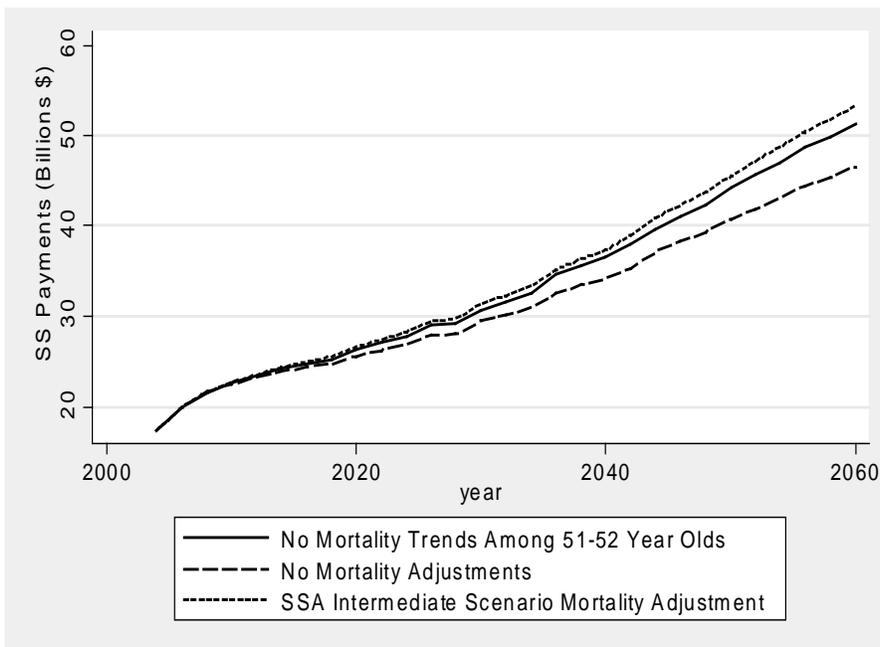

Figure 17: SSI Payment Forecast (for Age 51+ Population)
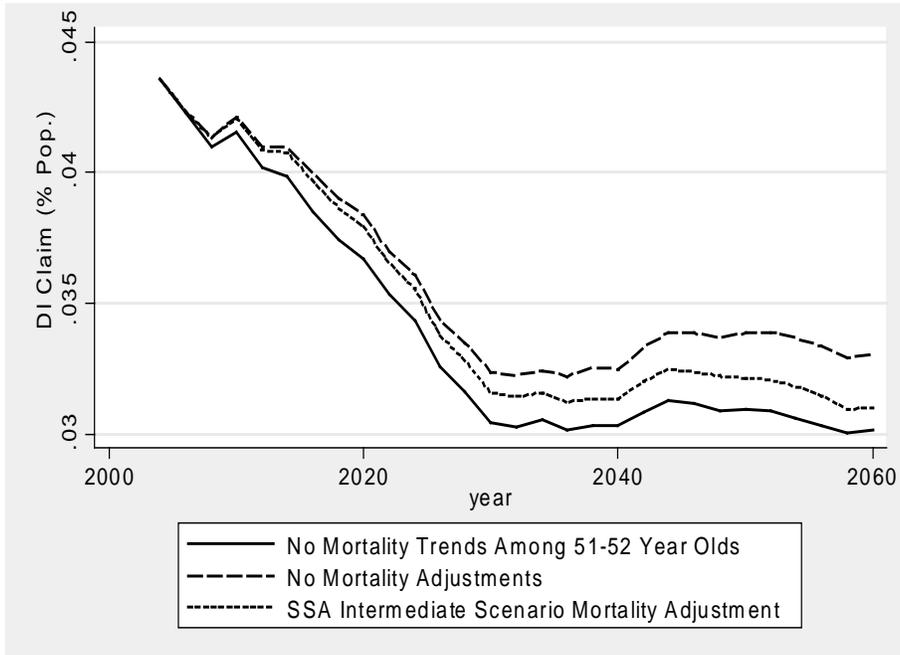
Figure 18: Proportion of Age 51+ Population Claiming DI
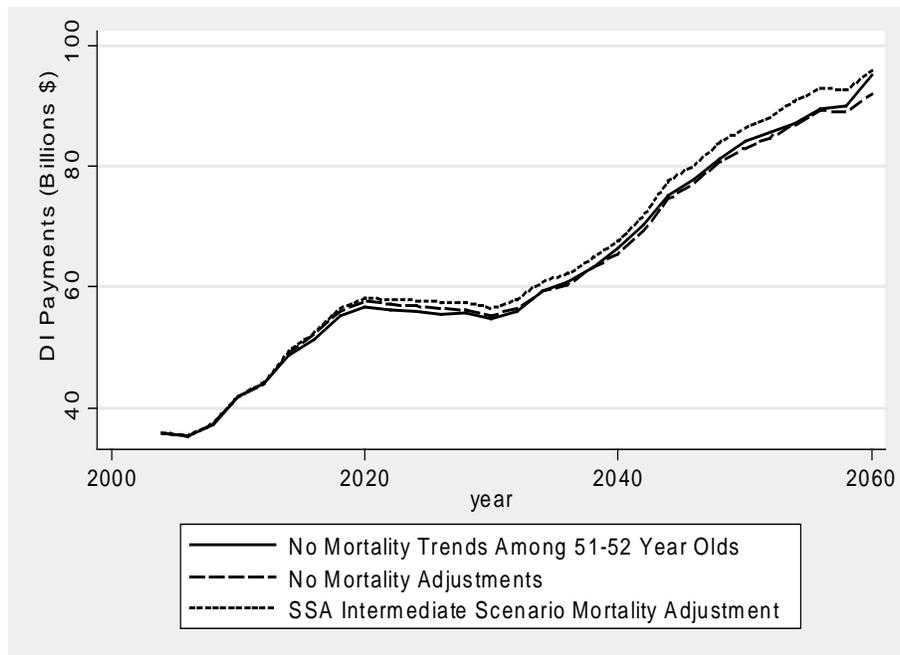

Figure 19: DI Payment Forecast (for Age 51+ Population)

Table 1. Estimated Transition Models in FEM version 1.0 (Log-hazard parameters)

	Cancer	Heart	Stroke	Hypertension	Diabetes	Lung	Arthritis
Cancer (t-1)			-0.11				
Heart disease (t-1)			0.26^3				
Stroke (t-1)							
Hypertension (t-1)		0.47^3	0.37^3				
Diabetes (t-1)		0.25^3	0.26^2	0.23^3			
Lung (t-1)							
Age<77 (spline)	0.05^3	0.07^3	0.06^3	0.04^3	0.05^3	0.04^3	0.04^3
Age>77 (spline)	-0.01	0.02^3	0.02^3	0.01	-0.05^3	0.01	0.01
Ever smoked	0.14^1	0.04	0.21^2			0.72^3	
Under Weight		0.09	0.31^3	-0.23^3	-0.22^2		-0.34^3
Obese		0.24^3	-0.10	0.29^3	0.71^3		0.26^3
Male	0.39^3	0.15^2	0.09	-0.21^3	0.06	-0.08	-0.29^3
Black	-0.07	-0.03	-0.04	0.47^3	0.23	-0.44^2	0.13
Hispanic	-0.33^1	-0.11	-0.26	0.26^2	0.42^2	0.28^1	0.01
HS drop-out	0.08	0.11^2	0.21^2	0.12^2	0.20^2	0.18^2	0.09^1
College graduate	0.13	-0.04	-0.22	-0.16^1	0.12	-0.25^1	0.04
Constant	-8.4^3	-8.8^3	-9.68^3	-5.93^3	-8.57^3	-8.08^3	-5.52^3
ln-L	-3799	-5402	-3185	-4877	-2861	-3047	-6277

NOTE: Asymptotic standard errors in parentheses; Significance: '1'=10%; '2'=5%; '3'=1%. Empty cells indicate clinically imposed restrictions—for example, we do not allow heart disease to affect diabetes, but we do allow diabetes to affect the likelihood of developing heart disease.

Table 2. Results of Mortality Estimation in FEM Version 1.0
(Log-hazard parameters and relative risks)

	Log-hazard coefficients		Percent hazard changes
	Male	Female	
Age<77	0.0547 ***	0.0932 ***	
Age>77	0.0641 ***	0.0707 ***	
Constant	-7.9263 ***	-11.2608 ***	
	(0.8371)	(0.9688)	
Cancer		0.3199 ***	37.70 ***
Heart disease		0.4103 ***	50.73 ***
Stroke		0.3785 ***	46.01 ***
Alzheimer's		0.8654 ***	137.60 ***
Diabetes		0.5044 ***	65.60 ***
Lung		0.3557 ***	42.72 ***
Arthritis		-0.2727 ***	-23.87 ***
Hypertension		-0.0039	-0.39
ADL>=1		0.2766 ***	31.86 ***
ADL>=3		0.3711 ***	44.93 ***
Ever smoked		0.1785 ***	19.54 ***
Under weight		0.4428 ***	55.71 ***
Obese		-0.0961	-9.16
Black		0.0716	7.42
Hispanic		-0.2753 **	-24.07 **
High school drop-out		0.1172 **	12.43 **
College graduate		-0.2564 ***	-22.62 ***
ln-L		-7511.37	

NOTE: Asymptotic t-statistics in parentheses; Significance: '*'=10%; '**'=5%; '***'=1%.

Table 3. Goodness of Fit for the Future Elderly Model - v2.0
(HRS Data - Controls for Unobserved Heterogeneity and Left-Censoring)

Outcome	Percent:		
	1992 (Observed)	2004 (Observed)	2004 (Simulated)
Survival	1	87.9	85.7
Chronic condition prevalence (%)			
Cancer	4.8	14.7	15.4
Diabetes	8.4	20.6	18.6
Heart disease	10.7	25.7	25.8
Hypertension	32.3	56.8	55.7
Lung disease	6.0	13.0	12.9
Stroke	2.1	7.0	7.6
Any chronic condition	46.0	72.2	77.1
3+ chronic conditions	3.4	16.1	14.7
Functional status			
IADL limitation only	7.2	2.4	3.0
1 or 2 ADL limitations	9.0	8.4	7.8
3 or more ADL limitations	0.0	3.0	2.1
Nursing home residency	0.0	0.8	0.4
BMI status			
Obese (BMI >=30)	23.2	29.5	26.4
Overweight (25 <=BMI<30)	39.9	40.2	39.5
Smoking status			
Ever-smoked	62.8	60.3	60.1
Smoking now	25.7	13.2	13.7

Notes: Estimation conducted with half of the 1992 HRS cohort. Outcomes are then simulated for the second half of the cohort and shown here.