

Statistical Security for Social Security

Samir Soneji · Gary King

© Population Association of America 2012

Abstract The financial viability of Social Security, the single largest U.S. government program, depends on accurate forecasts of the solvency of its intergenerational trust fund. We begin by detailing information necessary for replicating the Social Security Administration's (SSA's) forecasting procedures, which until now has been unavailable in the public domain. We then offer a way to improve the quality of these procedures via age- and sex-specific mortality forecasts. The most recent SSA mortality forecasts were based on the best available technology at the time, which was a combination of linear extrapolation and qualitative judgments. Unfortunately, linear extrapolation excludes known risk factors and is inconsistent with long-standing demographic patterns, such as the smoothness of age profiles. Modern statistical methods typically outperform even the best qualitative judgments in these contexts. We show how to use such methods, enabling researchers to forecast using far more information, such as the known risk factors of smoking and obesity and known demographic patterns. Including this extra information makes a substantial difference. For example, by improving only mortality forecasting methods, we predict three fewer years of net surplus, \$730 billion less in Social Security Trust Funds, and program costs that are 0.66% greater for projected taxable payroll by 2031 compared with SSA projections. More important than specific numerical estimates are the advantages of transparency, replicability, reduction of uncertainty, and what may be the resulting lower vulnerability to the politicization of program forecasts. In addition, by offering with this article software and detailed replication information, we hope to marshal the efforts of the research community to include ever

S. Soneji (✉)

The Dartmouth Institute for Health Policy & Clinical Practice and The Norris Cotton Cancer Center,
Dartmouth College, One Medical Center Drive, Lebanon, NH 03756, USA
e-mail: samir.soneji@dartmouth.edu

G. King

Institute for Quantitative Social Science, Harvard University, 1737 Cambridge Street, Cambridge, MA
02138, USA
e-mail: King@Harvard.edu

more informative inputs and to continue to reduce uncertainties in Social Security forecasts.

Keywords Forecasting · Mortality · Obesity · Smoking · Social Security

Introduction

Social Security, formally known as “Old-Age, Survivors, and Disability Insurance” (OASDI) is currently the single largest program in the U.S. federal government, with outlays in 2008 exceeding \$616 billion and representing 21% of total outlays (United States Government 2009). Social Security affects the lives of nearly every family through workers contributing payroll taxes; disabled workers, retired workers, and their dependents receiving benefits; and survivors of eligible beneficiaries who also receive benefits. A majority of elderly beneficiaries’ income is derived from Social Security benefits (Schneider 1999). In 2008, contributions through payroll taxes exceeded \$689 billion. Just under 42 million people received \$509 billion in Old-Age and Survivors Insurance (OASI) program benefits. An additional 9 million people received \$106 billion in Disability Insurance program benefits.

The magnitude of the Social Security program and variability of its inflows and outflows, owing especially to changes stemming from the aging baby boom population now entering retirement age, make the program’s financial health an ongoing political, social, economic, and policy issue. Indeed, demographic shifts in the last century are at the heart of current concerns over Social Security. As the large post-World War II birth cohorts aged and experienced declining mortality, the U.S. population aged. Fewer workers supported more beneficiaries, placing increased strain on Social Security trust funds. The Social Security Administration (SSA) is acutely aware of the importance of demographic shifts and is especially concerned about the pace of decline in future mortality.

In this article, we propose an alternative method of forecasting mortality that may be an improvement over current methods. Mortality forecasts are a crucial component—indeed one of the most uncertain large components—of the annual Social Security and Medicare projections mandated by Congress. We apply state-of-the-art Bayesian forecasting methodology that emphasizes smoothness in age-specific mortality rates and age profiles and incorporates potentially informative covariates. We demonstrate the utility of the new methodology in cause-specific and all-cause mortality forecasting. We also offer previously unavailable information that researchers need to replicate SSA’s exact mortality forecasting procedures and calculations. To forecast the mortality component of their projection, the SSA employs a complex, multistep process based largely on expert opinion about future rates of cause-specific mortality declines. These opinions involve expert assessments and weighting of information about demographic patterns, risk factors, and other considerations they deem important while attempting to preserve the smoothness of mortality age profiles. The SSA developed these finely tuned qualitative procedures over many years, which emphasize the empirical regularity of recent historical mortality, to compensate for the absence of sufficiently powerful formal statistical procedures.

Although improving on all the SSA's informal procedures would be difficult, the methodological literature has finally caught up with some aspects of informal approaches to forecasting. We thus use some of these new formal statistical methods, designed specifically for mortality forecasting. This is especially advantageous because informal forecasts may be intuitively appealing (Morera and Dawes 2006), but they suffer from humans' well-known poor abilities to judge and weight information informally (Dawes et al. 1989). Indeed, a large literature covering diverse fields extending over 50 years has shown that formal statistical procedures regularly outperform informal intuition-based approaches of even the wisest and most well-trained experts (Grove 2005; Meehl 1954). (There are now even popular books on the subject, such as Ayres (2008).)

Our approach formally incorporates the largest known risk factors with biological effects (tobacco consumption and obesity) and key demographic patterns (such as the fact that mortality rates in adjacent age groups tend to be very similar). The goal is not only more direct, transparent, and replicable forecasts. We also seek to enable the research community to build on our results with new sources of information and better statistical specifications than ours so that financial forecasts of the OASI and SSDI Trust Funds can continue to improve over time. To accomplish this task, we are making available, as a companion to this article, easy-to-use open-source software tools and all data and information necessary to replicate and extend our analyses (King and Soneji 2011b). The uncertainties of forecasting remain high, of course. However, enabling SSA and other researchers to easily build on our results and include more biological and demographic information will likely improve on our forecasting performance even further.

Researchers have studied how Social Security solvency forecasts depend on a variety of assumptions, and two large-scale simulation programs let users adjust some assumptions and study their effects. The "Stochastic Social Security Simulator" (Lee et al. 2003) and "Social Security and Accounts Simulator" (SSASIM) (Holmer 2003) allow adjustment of tax rates, retirement ages, and equities investment, but neither allows users to change SSA's hard-coded mortality forecasts. Two other programs, the SSA Office of Chief Actuary simulation program and the Congressional Budget Office Long-Term Actuarial Model, have restricted use and also hard-code their mortality forecast inputs (Burdick and Manchester 2003; Congressional Budget Office 2001; Meyerson and Sabelhaus 2000.) Fortunately, we were able to contract with the producer of SSASIM to modify his program and allow for the input of alternative mortality forecasts. SSASIM is widely used by academic researchers and U.S. government agencies, including the Government Accounting Office, Department of Labor Benefits Security Administration, and the SSA Office of Retirement and Disability Policy.

Social Security Administration Forecasts

Whereas the broad outlines of how the SSA produces its congressionally mandated annual forecasts of Social Security solvency are publicly available, details sufficient to allow replication of the SSA's procedures are not. Gathering these details with enough specificity was made possible through extensive research and considerable help from SSA actuaries and others involved in the process.

We begin with background information about trust fund financing, both payroll tax receipts and outlays to beneficiaries. We then turn to details of the SSA's mortality forecasts, including recent methodological critiques. Finally, we give mechanics of how to reproduce the SSA's trust fund forecasts.

Financing Background

In 1935, Social Security began as a social insurance program designed to pay workers aged 65 and older a continuing income after retirement (SSA Historian's Office 2007). The SSA began depositing revenue generated from the Federal Insurance Contributions Act taxes in 1937, and monthly payment benefits began in 1940 to elderly retirees under the Old-Age Survivors Insurance (OASI) program. In 1954, Congress passed the Social Security Amendments, which established the Social Security Disability Insurance (SSDI) program for workers unable to work because of disability.

Since 1954, Social Security has consisted of two separate programs, OASI and SSDI, and operates as a partially advanced funded (modified pay-as-you-go) system in which workers' earnings are subject to OASI and SSDI payroll taxes up to a fixed maximum in taxable earnings. The revenue is deposited into OASI and SSDI Trust Funds that pay benefits to qualified elderly retirees and disabled workers, respectively. Surplus revenue is borrowed by the U.S. Treasury, which in turn issues special-issue Treasury bonds to Social Security.

OASI and SSDI payroll taxes have gradually increased since their inception in 1937 and 1954, respectively (Table 1). Along with changes in age and income distributions, increases in payroll taxes contributed to revenue in excess of expenditure, leading to surplus. Beginning in 1972, Social Security trustees became concerned about short-term insolvency because of a weak economy and expected long-term insolvency from an aging population (Ball 1973; SSA Historian's Office 2010). In

Table 1 OASI and SSDI Trust Funds

| Year | OASI | | | | SSDI | | | |
|------|-----------------|----------------|--------------------|---------|-----------------|----------------|--------------------|---------|
| | Payroll Tax (%) | Total Receipts | Total Expenditures | Balance | Payroll Tax (%) | Total Receipts | Total Expenditures | Balance |
| 1940 | 2.00 | 0.37 | 0.06 | 2.03 | — | — | — | — |
| 1950 | 3.00 | 2.93 | 1.02 | 13.72 | — | — | — | — |
| 1960 | 5.50 | 11.38 | 11.20 | 20.32 | 0.50 | 1.06 | 0.60 | 2.29 |
| 1970 | 7.30 | 32.22 | 29.85 | 32.45 | 1.10 | 4.77 | 3.26 | 5.61 |
| 1980 | 9.04 | 105.84 | 107.68 | 22.82 | 1.12 | 13.87 | 15.87 | 3.63 |
| 1990 | 11.20 | 286.65 | 227.52 | 214.20 | 1.20 | 28.79 | 25.62 | 11.08 |
| 2000 | 10.60 | 490.51 | 358.34 | 930.00 | 1.80 | 77.92 | 56.78 | 118.46 |

Notes: Payroll tax, total receipts, total expenditures, and end-of-year total balance for the OASI and SSDI programs for select years. Total receipts include contributions, income from taxation of benefits, and interest on the trust funds. Total expenditures include benefit payments, administrative expenses, and transfers to the Railroad Retirement program. Inlays, outlays, and balances are reported in nominal billion dollars.

1983, Congress raised payroll taxes considerably to allow the program to better meet its long-term financial obligations. Combined OASI and SSDI payroll tax rates grew from 10.8% to 12.4% between 1983 and 1990 and have remained constant since. As a result of payroll taxes that generated revenue in excess of annual benefit outlays over the last 25 years, the trust funds have amassed large surpluses in preparation for the aging population.

Presently, the SSA is suggesting an increase in payroll tax rates as one of many possible provisions to address long-range solvency problems (TBOT 2007). Other broad policy options include changes in cost-of-living adjustment, changes in the level of monthly benefits, increasing retirement age, investment in marketable securities, greater taxation of benefits, and substitution of individual accounts for some part of currently scheduled benefits (Chaplain and Wade 2005).

The prospect of insolvency raises several important legal issues on the rights of beneficiaries to receive full Social Security benefits. The Social Security Act (42 U.S.C. § 401(h)) stipulates benefits be paid from accumulated trust fund assets and current payroll. Yet, if future benefits exceed remaining trust fund assets and payroll tax revenue, the Antideficiency Act (31 U.S.C. § 1341) prohibits government spending in excess of available funds (Swendiman and Nicola 2008). The likely outcome of such a scenario would be a reduction in benefits or delayed payment of full benefits (Romig 2008).

Mortality Forecasting

The Office of the Chief Actuary (OACT) employs a multistep process to produce age- and sex-specific mortality forecasts 75 years into the future (Bell and Miller 2005). The OACT produces mortality forecasts annually as a key input to solvency projections published in annual SSA OASDI Trustees Reports (see Olshansky 1988; Wilmoth 2005b). Current SSA mortality forecasts are based on a combination of linear extrapolation from historical data and labor-intensive subjective choices of 70 interrelated ultimate rates of decline, which are appraised by the OACT (civil servants) and ultimately approved by the OASDI trustees (political appointees) (Wade 2010).

Although in our experience SSA officials are exceptionally careful, the process is challenging, cumbersome, and intrinsically error-prone. Given normal human biases and cognitive limitations, the process can be affected by political or other considerations, which, in turn, can affect substantive policy choices in unintended ways. The SSA chose this approach as the best option available at the time because appropriate formalized approaches were not available.

The current SSA forecasting process works as follows (each of the details is crucial, since different choices at each stage can greatly affect forecasts). First, the OACT collects cause-specific death and population counts between 1980 and 2006 (the most recent year of mortality data available) to calculate cause-specific mortality rates by age and sex. Cause-of-death information comes from U.S. vital statistics and is based on the Ninth and Tenth Revisions of the International List of Diseases and Causes of Death. The categories of causes are heart disease, cancer, vascular disease, violence, respiratory diseases, diabetes mellitus, and a residual category of all other causes. Population counts for those under age 65

come from U.S. Census intercensal data, and for those ages 65 and older come from Medicare enrollment data.

Second, the cause- and sex-specific central death rate is calculated for age groups 0–1 and 1–4, and for five-year age groups thereafter. Age 95 is the start of the open final age interval. The central death rate is the weighted average of mortality rates in the age group, with weights equal to the population count of a given age. The result is 294 cross sections of age group-, sex-, and cause-specific mortality.

Third, the SSA OACT forecasts the annual reduction of the central death rate by age group, sex, and cause through a combination of linear extrapolation and subjective judgment. They fit a least squares line to the logged central death rate as a function of the year. The average annual percentage reduction is the complement of the exponential of the slope (Bell and Miller 2005). Then they assign an ultimate annual percentage reduction of sex- and cause-specific central death rates, 75 years after the projection period begins, for the broad age groups under 15 years old, 15–49, 50–64, 65–84, and 85 and older. The SSA selects ultimate rates of decline based on subjective assessment. Next, through a complicated trial-and-error process performed by the OACT, an ultimate rate of decline is adjusted so the resulting forecast 75 to 80 years in the future is considered “reasonable.” In total, there are 70 such ultimate rates of decline—five broad age groups, two sexes, and seven causes of death.

Fourth, for the years 2007 and 2008, the average annual reduction in the central death rate for a given age group, sex, and cause of death is assumed to equal the average annual reductions between the years 1980 and 2006. For 2009 to 2034, the log mortality rate decreases linearly from 100% of the average annual reduction from 1980 to 2006 to the ultimate reduction in 2034. If the average annual reduction from 1980 to 2006 is positive, the log-mortality rate decreases linearly from 75% of this initial average annual reduction to the chosen ultimate level in 2034. After 2034, the average annual reduction remains constant at the ultimate reduction level. In the final step, sex- and age group-specific central death rates are summed across causes of death. The final all-cause mortality is then used as the mortality input for subsequent OASI and SSDI solvency projections and SSDI disability termination rate projections. The SSA Chief Actuary provides a formal statement of actuarial opinion on the projection, its assumptions, and the methodology used to evaluate the financial and actuarial status of the trust funds.

The OACT evaluates the social, biological, environmental, and medical factors that may have affected historical mortality patterns (Wade 2010). The OACT then considers the influence of these factors and emerging factors on future mortality trends. Even for a single sex and cause of death, the SSA’s choice of five ultimate rates of decline is a challenging task. To the extent that this choice is based on the plausibility of the resulting forecasts, this choice makes all the other intermediate modeling procedures *irrelevant*. Figure 1 presents rates of decline by age group, sex, and cause of death based on mortality data between 1980 and 2006. Also shown are the ultimate rates of decline under the SSA intermediate projection.

Comparison between the historical and ultimate rates highlights important problems and concerns. First, the pattern across age of ultimate rates of decline differs considerably from historical pattern for several cause-sex groups. For example, the historical rate of decline for female respiratory disease declines steadily over age. Between ages 55 and 84, the historical rate of decline is negative (indicating

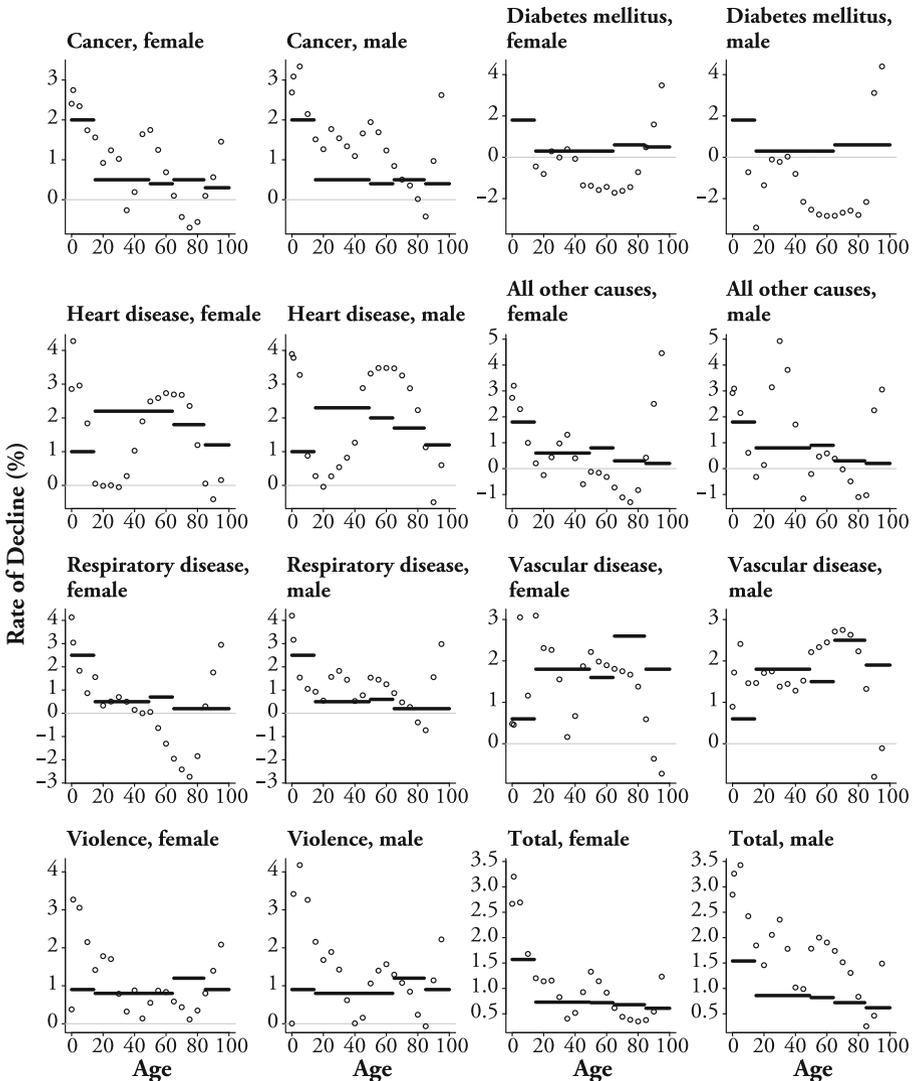


Fig. 1 Historical rates of decline and SSA intermediate cost ultimate rates of decline. Each panel shows the historical rate of decline (o) and SSA intermediate cost ultimate rate of decline (–) by age group and sex for a particular cause of death (cancer, diabetes mellitus, heart disease, all other causes, respiratory disease, vascular disease, violence) and for all causes

worsening mortality over time) and lowest for 75- to 79-year-olds, at -2.73% . Yet, the ultimate rate of decline for female respiratory disease is positive and considerably higher than historical rates of decline. For example, the ultimate rate of decline for 75- to 79-year-olds beginning in the year 2034 is over 100% greater, at $+0.2\%$. Emphysema death may decline in the future as a result of historic cigarette smoking declines. Yet, the leading causes of respiratory disease death, influenza and pneumonia, may not decline given the emergence of more virulent and multi-drug-resistant strains of influenza virus.

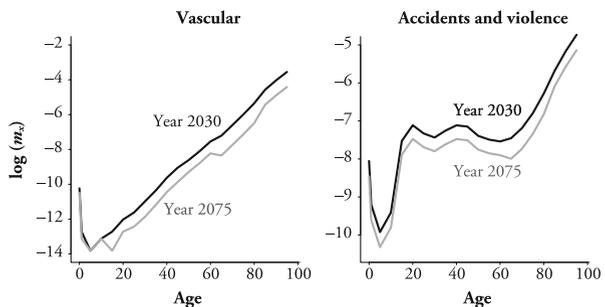
Second, the precise reasoning and justification used in the selection of an ultimate rate of decline for a particular age group, sex, and cause are not publicly available. For example, the ultimate rate of decline for childhood cancers (2.00% per year) is within the range of historical rates of decline (1.74% to 3.34%). Yet, why the ultimate rates of decline are lower and then higher than historical rates for adults is not known publicly. Also not known publicly is whether the ultimate rates of decline in adult cancer vacillate because of a substantive belief held by the SSA or instead because of necessary adjustment to achieve a smooth age profile. We observe a similarly curious vacillation in vascular disease mortality ultimate rates of decline. The ultimate rate of decline for male vascular disease mortality is posited to be 1.8% between ages 15 and 49, down to 1.5% between ages 50 and 64, up to 2.5% between ages 65 and 84, and back down to 1.9% for ages 85 and older. Finally, the ultimate rate of decline in injury accidents is equal for males and females and highest for the 65- to 84-year age group. Yet, historical rates of decline were highest for young adults, especially young adult males. Injury accidents are often the result of risky and impulsive behavior involving alcohol and motor vehicles. Thus, we might expect the ultimate rates of decline for this age group and cause to be higher, not equal, for males than for females.

Despite considerable time and effort in selecting 70 ultimate rates of decline, a plausible forecast when linearly extrapolated will eventually become increasingly implausible over time. Consider the year 2030 and 2075 SSA forecasts of male vascular disease mortality (Fig. 2, left panel). While the year 2030 forecast is reasonable from a historical perspective, and we would expect a decline in the level of vascular mortality, there is a considerable and unlikely drop in the year 2075 forecast age profile between ages 65 and 84. Another problem appears with male accidental and violent deaths (Fig. 2, right panel). Compared with the SSA's year 2030 forecast, the year 2075 forecast age profile is lower, as we would expect, but somewhat less smooth, especially around age 65.

Critiques of Social Security Forecasting Methodology

Demographers have raised several concerns about the SSA mortality forecasting methodology (Lee and Tuljapurkar 1997; SSABTP 1991, 1994, 1999, 2007; Wilmoth 2003). Both the 2003 and 2007 Technical Panels on Methods and Assumptions, convened by the congressionally appointed Social Security Advisory Board, recommended against forecasting cause-specific mortality rates because of the resulting

Fig. 2 Male vascular and accidental and violent death mortality, 2030 and 2075. Forecasts for 2030 appear as black lines, and those for 2075 appear as grey lines. Deaths attributable to vascular disease are in the left panel, and those attributable to accidental and violent death mortality are in right panel



difficulties in modeling the interdependencies among causes of death. The subjective choice of 70 ultimate rates of decline (five broad age groups, two sexes, and seven causes of death) introduces complexity and obscurity into the method as well (Wilmoth 2003, 2005b). The technical panel also noted that all-cause mortality forecasts change solely because of differences in the subjectively assigned ultimate rates of decline. Additionally, because of the SSA's implementation of cause-specific forecasting, an inherent convergence occurs in the overall decline to the most slowly declining cause of death because an increasing proportion of deaths become attributed to this cause (Wilmoth 1995, 2003, 2005b).

Another critique focuses on independently forecasting age-specific mortality cross sections despite the obvious dependence among them. A forecast derived in this manner may quickly depart from historical patterns (Keyfitz 1982; McNown 1992). To partially mitigate this problem, the SSA assigns an ultimate rate of decline for broad age groups based on informal judgments (Alho 1992). In a study of forecast accuracy, Alho and Spencer (1990) noted that even simple linear extrapolations often outperform SSA forecasts (although that does not necessarily imply that linear extrapolations should be used instead). Lee and Miller (2001) noted that the SSA mortality projection and other long-run government forecasts that rely on informal expert judgment have proven too pessimistic about the future.

SSA mortality forecasting methodology includes risk factors and known demographic patterns through the qualitative judgments of experts, which has the advantage of including both key sources of information but also carries the disadvantages of informality discussed above. The most commonly used methods in the literature, which the SSA would have had at its disposal, have the advantage of being more formal and replicable but exclude information about risk factors and demographic patterns. Purely extrapolative methods could yield forecasts that maintain long-standing patterns of smooth mortality time trends, although most violate smoothness in the age profile and, by construction, exclude key information, such as known risk factors. Forecasting methods incorporating these risk factors as covariates do so by assuming independence among age groups. Typically, these methods produce forecasts that violate known demographic patterns, such as the fact that adjacent age groups have similar mortality rates. Better mortality forecasting approaches that formally incorporate additional information while simultaneously preserving quintessential demographic patterns were not available to the SSA.

Solvency Simulations

Each year, the Board of Trustees for the OASI and SSDI Trust Funds provides three long-range (75-year) sets of assumptions on demographic, economic, and program-specific conditions. The intermediate set represents the Trustees' best estimate for future experience. The low-cost set assumes relatively rapid economic growth, low inflation, and favorable demographic conditions from the standpoint of program financing. The high-cost set assumes relatively low economic growth, high inflation, and unfavorable demographic conditions (Cheng et al. 2004).

The first broad category of assumptions is demographic and comprises the total fertility rate, rates of decrease in the central death rate for two sexes and 21 age groups, legal immigration, legal emigration, and net other immigration. The second

broad category is economic and comprises the unemployment rate, inflation rate, real interest rate, percentage change in real average wage, disability incidence for males and females, and disability recovery for males and females. The SSA Office of the Chief Actuary stochastically projects long-term finances by first assigning random variation to these key demographic and economic assumptions (Cheng et al. 2004). The simulation consists of nine sequential modules in which the output from a previous module is the input to a later module. Within a run of the simulation, the model of Social Security finance projections is deterministic.

In a given run of the simulation, demographic assumptions are used to project a whole population. Then, the population is combined with economic assumptions to create an economic module. The population and economic modules are used to simulate information on the fully insured and disability insured. Next, the population and economic modules are used as inputs in the awards module, which provides information on newly entitled worker benefits. Finally, all previous modules are used in the costs module to produce annual solvency projections.

To implement these procedures, we use an implementation by the Policy Simulation Group (Holmer 2008). We alter only mortality forecasts and set all other assumptions at the intermediate level chosen in the 2008 SSA Trustees Report (TBOT 2008), based on mortality data up to the year 2006, the last year of available national mortality data from the U.S. National Center for Health Statistics. In this way, we can directly attribute differences in solvency measures to differences in mortality forecasts alone.

Formal Statistical Forecasts of Mortality

Throughout our mortality forecasting method, we attempt to follow the best forecasting practice, as it exists in most fields. We do not attempt to estimate causal effects of specific risk factors; that requires different types of statistical models. We instead use key available knowledge, although necessarily partial, of biological processes and demographic patterns to forecast based on empirical regularities built on what is known. We thus marshal the best existing micro-level evidence on mortality risk factors and demographic patterns to choose covariates and set Bayesian priors. The result is not an ironclad or internally complete forecasting model without error, since scientific knowledge of mortality is not up to that task. Nothing guarantees that what was empirically regular will remain so, but without better theory, the best one can do is to incorporate as much information available now to understand the future. What distinguishes our forecasting approach is that our models are able to incorporate considerably more information.

We begin by discussing the key information we are able to formalize and include in our models—demographic patterns and risk factors with known biological consequences—and then summarize our statistical approach that includes all these features. Our goal is to make it possible for others to improve the specifications we chose, and so the patterns and risk factors discussed in this section are intended primarily as examples of what can be included, but also a summary of what we actually used to generate our empirical results.

Demographic Patterns

Demographic research spanning hundreds of years has repeatedly identified three ubiquitous patterns in the vast majority of countries and time periods studied (Boyer 1947; Gompertz 1825; Graunt 1662; Halley 1693; Vollgraff 1950). First, age-specific all-cause mortality rates trend (and usually decline) smoothly and gradually over time; patterns are not always linear, but they have few sharp jumps from one year to the next. Notable exceptions include large epidemics and pandemics (e.g., the Spanish influenza pandemic of 1918–1919), although such events have been historically rare. Second, time-specific all-cause mortality rates (i.e., age profiles) are smooth and so do not jump sharply between adjacent age groups. Finally, age profiles of all-cause mortality have a characteristic shape: log mortality starts high at birth, drops to about age 10, and then increases from there on, usually with a temporary “bump” during the 20s that is often attributed to accidents and is especially prominent for males. Of course, these patterns need not continue, and the future may differ from the past, but they have been so prevalent for so long that it seems wise to build forecasting models that maintain these patterns unless they are rejected by the data. Thus, the forecasting approach will miss some future patterns, but the parts missed will ideally be those for which no prior indication was available.

Risk Factors With Known Biological Consequences: Smoking and Obesity

Cigarette tobacco consumption and obesity are two major risk factors with important biological links to higher disability rates and lower earnings during working years, as well as higher mortality risk after retirement. Crucial for forecasting, the prevalence of both is in the process of considerable change in the U.S. population.

Smokers contribute less in payroll taxes primarily through higher absenteeism (Ryan et al. 1992), lower earnings (Levine et al. 1997), and greater work disability (Sloan et al. 2004). Doll et al. (1994) found that smokers after retirement experienced a higher mortality rate than their similarly aged nonsmoking counterparts. On balance, smokers contribute more to Social Security in payroll taxes than they receive in SSDI and OASI benefits (Sloan et al. 2004). Consequently, smokers represent a net financial gain for the Social Security Trust Funds (Gravelle 1998). Sloan et al. (2004) show that the steady declines in tobacco consumption alone could reduce the net gain and translate into increased Social Security cost.

As with tobacco consumption, obesity is strongly linked to earnings, disability, and mortality. Obese women, notably white obese women, likely face discrimination based on their weight and experience greater work limitations that result in lower earnings compared with non-obese women (Cawley 2004). Evidence regarding an income disadvantage for obese men is inconclusive. The obese, especially the morbidly obese, experience much greater risk of mortality, notably in mortality from cardiovascular disease (Flegal et al. 2007) and ischemic stroke (Suk et al. 2003). Stewart et al. (2009) estimated that continuing increases in obesity will “increasingly outweigh” the gains in mortality declines attributable to reductions in smoking. Whether the obese represent a net financial gain to Social Security remains an open question. Much depends on future obesity levels and how the obese population’s reduced earnings, increased work disability, and greater mortality risk are currently

distributed across the life course and will be distributed in the future (Adams et al. 2006; Reuser et al. 2008; Thorpe and Ferraro 2004).

Between 1955 and 2006, male and female smoking rates steadily declined for all age groups. Young adult males experienced the sharpest declines. In contrast, both sexes experienced a dramatic increase in obesity, starting about 1980, with the sharpest increases occurring among the young. See King and Soneji (2011a) for full details on smoking and obesity data sources, measurement and estimation, and how these covariates were incorporated into the mortality forecasting model.

Statistical Modeling

We use a mortality forecasting methodology developed and applied in King and Soneji (2011a), extending work by Girosi and King (2008). This formal Bayesian statistical model can incorporate existing demographic patterns as quantitative priors and risk factors as covariates. If the data do not support the chosen priors or covariates, they are automatically down-weighted or ignored in making forecasts. The model is specialized so that the priors are about expected mortality, which we know a great deal about from prior research. In contrast, classical Bayesian approaches require priors on coefficients, about which little is known. (The priors on expected mortality induce a prior on the coefficients for purpose of computation, but with many fewer adjustable hyperparameters.) It would be incorrect to claim that subjective expert judgment is avoided in building this or any statistical model, but its role here is formalized and transparent, and it is limited as much as possible to those areas where information is available.

A relatively small component of forecasting uncertainty is due to estimation uncertainty—that is, the portion of uncertainty that results from not knowing the values of the parameters of the assumed model (which is why research on mortality forecasting models, including ours, dispenses with traditional confidence intervals, which are solely based on estimation uncertainty, assuming the model is true). Rather, the primary uncertainty in forecasting comes from “model dependence” that results from not knowing the exact model, such as in the choice of covariate, lag, and prior specifications (King and Zeng 2006). We pay special attention to the uncertainty resulting from choices we make in the Bayesian priors, which represent the knowledge that expected mortality is smooth over time and over age groups. (King and Soneji (2011a) also studied model dependence as a function of covariate and lag length choices.) We study this prior uncertainty with a version of “robust Bayesian analysis.” This standard procedure uses a class of priors instead of only one, the result being a range of many forecasts that better reflects uncertainty (because it includes model uncertainty) instead of a single point estimate.

Our model uses as covariates a time trend, cohort smoking prevalence lagged by 25 years in age and time, and cohort obesity prevalence lagged by 25 years in age and time. The time trend is a simple proxy for technological change; it is possibly inadequate but consistent with common practice in the literature. (We have also experimented with other indicators based on medical patents and citations but have not as yet found major differences.) We have three reasons for our choice of lag length for smoking and obesity. First, we use 25-year lags so we can forecast 25 years into the future through a standard one-step-ahead forecast without needing to forecast

values of the covariates, which would have introduced far more (unnecessary) uncertainty into the process. Second, an extensive life course literature on the timing of exposure and eventual mortality outcomes supports approximately the same lag length (Gutterman 2008; Peace 1985; Sturm 2002). And third, King and Soneji (2011a) conducted detailed analyses on lag length and covariate specification and found empirically that forecasts are quite robust to changes in lag length.

Period effects may also strongly affect mortality. For example, the 1964 U.S. Surgeon General's Report on Smoking and Health marked a period of intense anti-tobacco public health campaigns. Unlike a cohort-specific model, which incorporates time-lagged correlation between potential covariates and mortality, a period-specific model would require the prediction of covariates for ages in the future. Also noteworthy is the current debate within the demographic research community on whether period life expectancy is biased because of changes in the timing or age of mortality (Bongaarts and Feeney 2003; Guillot 2003; Wilmoth 2005a). Such changes in the timing of death may result, for example, from the considerable decline in U.S. smoking.

In the left panels of Fig. 3, we compare our forecast interval of expected age at death, portraying prior specification uncertainty (the grey lines), with projections by the SSA low-, intermediate-, and high-cost mortality scenarios (see the five crosses, with a horizontal line at the intermediate scenario). In a period life table, the expected age at death equals the sum of life expectancy and age.

Results indicate that we forecast expected ages at death to be older than the SSA intermediate-cost mortality scenario and similar to the SSA high-cost mortality scenario. For example, at age 0 in the year 2030, we forecast the male expected age at death to be between 78.9 and 79.5 years, compared with the intermediate- and high-cost scenario projections of 77.6 and 79.4 years, respectively (TBOT 2006). In the two graphs in the middle column of Fig. 3, we compare our forecast age-of-death distributions with SSA's low-, intermediate-, and high-cost scenarios. Compared with SSA projected age-of-death distributions, our forecast age distributions are considerably older. As a result, the aged dependency ratio (the ratio of the age 65+ population to the age 20–64 population) is larger, as shown in the right panel of Fig. 3. For example, in 2030, we forecast 40.5 to 41.7 elderly per 100, compared with an SSA intermediate-cost projection of 39.5 (low-cost 37.0 and high-cost 42.4). The larger ratio implies greater strain on the working-age population and Social Security, which relies on intergenerational transfers of wealth.

Validation and Assessment of Formal Statistical Mortality Forecast

We supplement the numerous out-of-sample validation tests in Girosi and King (2008) in several ways. First, we use the well-established relationship between cigarette smoking and cancer mortality (Doll et al. 2004; Peace 1985; Preston and Wang 2006; Wang and Preston 2009). Using multiple-cause-of-death detail files and Human Mortality Database population counts, we calculate historical cancer-specific conditional probabilities of mortality. We set aside the most recent 5 years of observed mortality, 2003–2006, as a validation period and base our formal statistical forecast on earlier historical data, 1980 to 2002. We compare our forecasts with SSA cancer-specific projections and a new forecast based on the Lee-Carter method (Lee

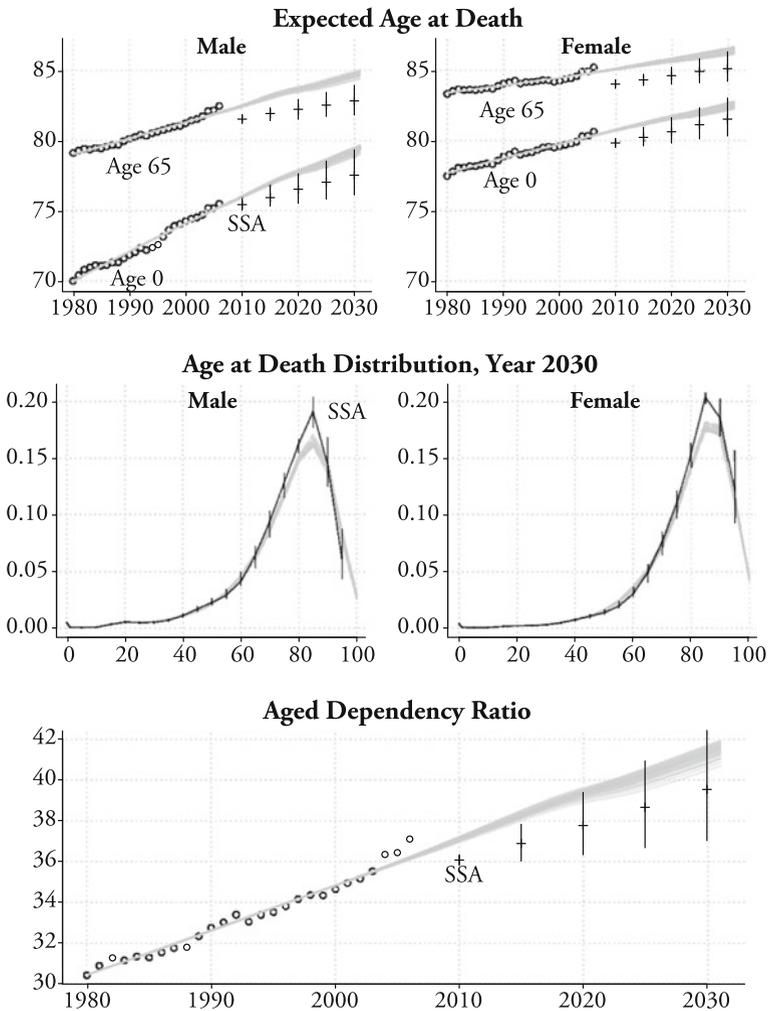


Fig. 3 Expected age at death, age distribution of deaths, and aged dependency ratio. For all panels, the grey lines of varying width represent our forecasts (with uncertainties because of prior dependence); other lines represent SSA forecasts (with uncertainties because of differences between SSA's low and high cost scenarios). The top panels give forecasts for males (*left*) and females (*right*) for expected age at death at ages 0 and 65. The middle row gives the male (*left*) and female (*right*) age at death distribution in 2030. Age groups are 0–1 and 1–4, and five-year age groups thereafter. The bottom panel gives forecasts for the ratio of elderly (65 and older) to the working-age population (20–64)

and Carter 1992), both using the same historical data. We compare the difference among our median forecast, the SSA intermediate cancer projection, and the Lee-Carter-based forecast with observed 2006 cancer mortality in Fig. 4. Although the new cause-specific forecast, based on the Lee-Carter method, is a departure from the original intent of their model, it is widely used and serves as an important point of comparison. Both statistical forecasts and the SSA intermediate projection accurately predict cancer mortality in 2006 between ages 0 and 40. The forecast error for females between ages 45 and 85 is approximately the same for both statistical forecasts and

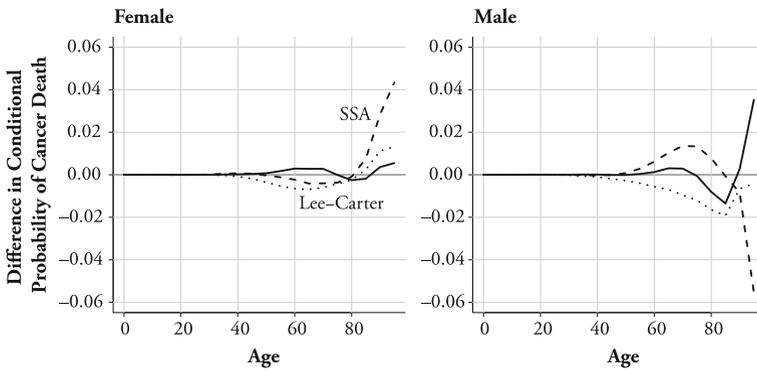


Fig. 4 Validation of formal statistical forecast and SSA projection against observed 2006 cancer mortality. Difference between our median cancer mortality forecast and observed 2006 cancer mortality (—), the SSA intermediate cancer projection and observed 2006 cancer mortality (---), and the Lee-Carter-based cancer mortality forecast and observed 2006 cancer mortality (⋯). Both forecasts and the projection are based on the same historical cancer data, 1980–2002. Observed cancer mortality from 2003 to 2006 is set aside for validation

the SSA projection. For males between ages 45 and 85, our forecasts are closer to observed mortality than both the Lee-Carter-based forecast and the SSA projection. The mean absolute error for our median forecast is 0.005, while equal to 0.008 for the Lee-Carter-based forecast and 0.011 for the SSA intermediate projection. Another important difference among our forecast, the Lee-Carter-based forecast, and the SSA projection is the incorporation of potentially informative medical, behavioral, and social covariates. Whereas we incorporate this information formally, and the SSA incorporates it informally, the Lee-Carter-based approach does not incorporate these covariates at all (but see the recent modified approach by Reichmuth and Sarferaz 2008). Thus, there is reason to believe that forecasts from our approach will continue to be accurate farther into the future.

Second, we perform a similar validation with all-cause mortality in Fig. 5. Our formal statistical forecast, the Lee-Carter-based forecast, and SSA intermediate

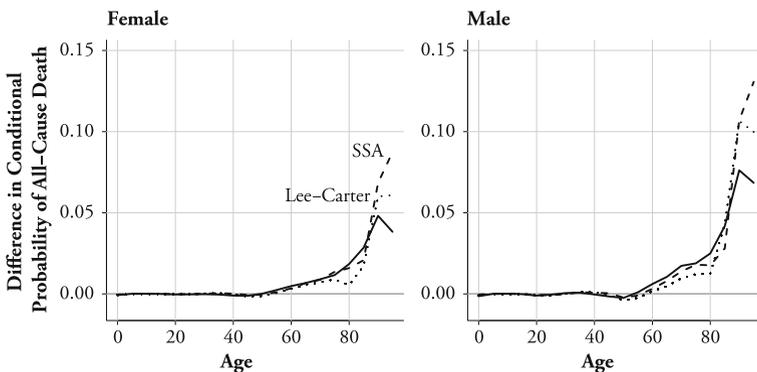


Fig. 5 Validation of formal statistical forecast and SSA projection against observed 2006 all-cause mortality. Difference between our median all-cause mortality forecast and observed 2006 all-cause mortality (—), the SSA intermediate all-cause projection and observed 2006 all-cause mortality (---), and the Lee-Carter-based all-cause mortality forecast and observed 2006 all-cause mortality (⋯). Both forecasts and the projection are based on the same historical data, 1980–2002. Observed mortality from 2003 to 2006 is set aside for validation

projection accurately predict 2006 all-cause mortality between ages 0 and 50. After age 50 for both males and females, forecast error grows with age for both forecasts and the SSA projection. The mean absolute error for our median forecast is 0.022, while it is 0.024 for the Lee-Carter-based forecast and 0.028 for the SSA intermediate projection. As previously noted, only our forecast and the SSA projection incorporate potentially informative covariates.

Third, we assess the smoothness of future mortality age profiles. For example, we consider male vascular disease. The level of age-specific vascular disease mortality has declined over time, likely as a result of more effective medical management and intervention of vascular disease (Burns et al. 2003) and reduced smoking (Wolf et al. 1998). Within a given year, the age profile of vascular disease mortality has maintained the same quintessential shape; this pattern may likely continue in the near future. In Fig. 6, we compare the 2030 age profile of our male vascular disease mortality forecast (left panel), the intermediate SSA projection (center panel and previously shown in Fig. 2), and Lee-Carter-based forecast (right panel). The age profile of our formal statistical model appears smooth over all ages. The SSA age profile is smooth before age 65. After age 65, the SSA intermediate projection begins to show nonsmooth behavior, which is inconsistent with historically observed age profiles. Finally, the Lee-Carter-based age profile is less smooth than either ours or the SSA projection. In addition to not incorporating potentially informative covariates, either formally or through subjective judgment, the Lee-Carter-based method considers each cross section of age-specific mortality independently, which will often result in nonsmooth age profiles.

Results on Social Security Solvency Measures

In this section, we forecast Social Security solvency measures. With the exception of alternative mortality forecasts, we use methodology identical to the SSA and invoke the same long-term demographic, economic, and policy assumptions. We then explore the effect of the mortality forecasts on future annual net income of the OASI and SSDI programs, trust fund balances, cost rates, and expenditure and cost as a percentage of gross domestic product (GDP). We leave all other demographic,

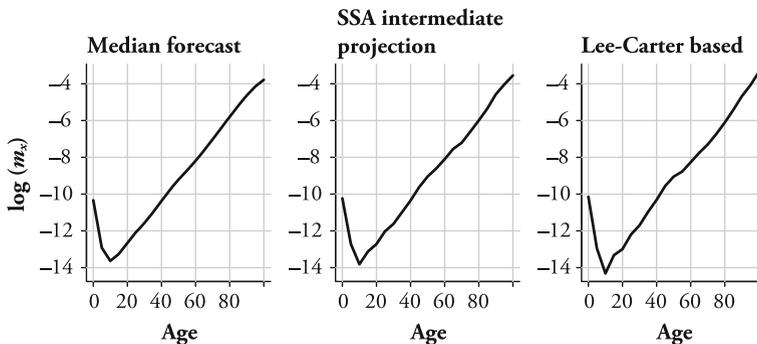


Fig. 6 Age profile of year 2030 male vascular disease mortality. Age profiles for our median mortality forecast (*left panel*), SSA intermediate projection (*center panel*), and Lee-Carter-based forecast (*right panel*)

economic, and program-specific parameters and variables set to their 2006 intermediate level. Finally, we assess the payroll tax rate required to offset annual benefit payments with the revenue generated from payroll taxes and interest from the trust fund. We adjust for projected inflation and report all figures in 2006 dollars.

Annual Net Income

The annual net income for the OASI and SSDI programs is equal to the sum of payroll tax revenue and income from interest less benefits paid and administrative costs. We forecast gradual gains in the combined OASI and SSDI annual net income until peak excess between \$201 and \$204 billion in 2012 (Fig. 7, upper-left panel). The annual net income then declines, and we estimate negative net income starting between 2023 and 2024. In comparison, combined annual net income under the SSA assumptions peaks between \$217 and \$218 billion in 2012 and first reaches negative net income between 2026 and 2027. By 2031, we estimate annual net income to be about $-\$217$ billion, with an uncertainty interval attributable to model dependence in forecasting mortality ranging from $-\$197$ to $-\$226$ billion (see Table 2). In comparison, annual net income is projected to be between $-\$93$ and $-\$172$ billion under the SSA assumptions in 2031.

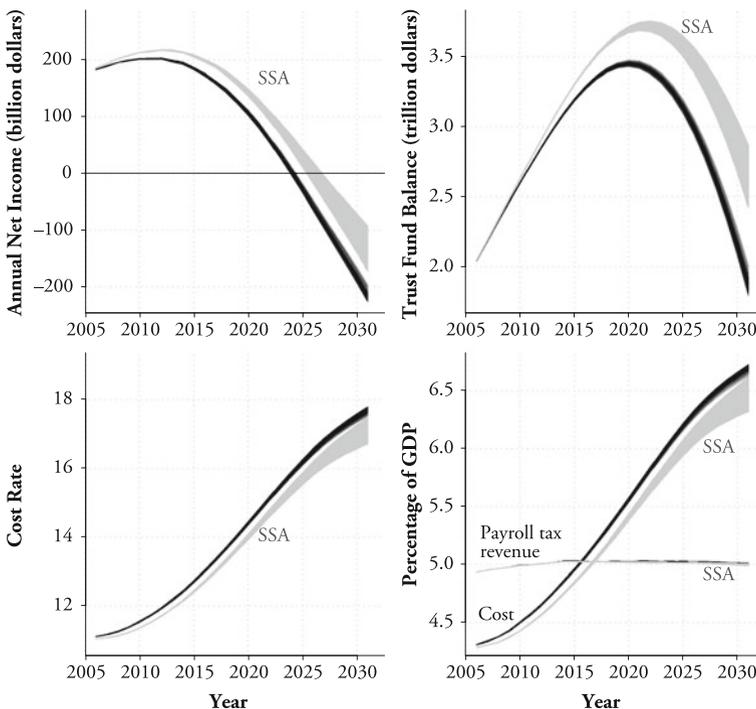


Fig. 7 Combined OASI and SSDI solvency: Annual net income, trust fund balance, cost rate, and cost and payroll tax revenue as a percentage of GDP. The upper left panel gives the combined OASI and SSDI annual net income for our forecasts (solid lines) and SSA (grey lines). The upper right panel gives differences in the combined OASI and SSDI Trust Fund balances. The lower left panel gives differences in the combined OASI and SSDI cost rates. The lower right panel gives differences in the payroll tax revenue and program costs as a percentage of gross domestic product

Table 2 Comparison of our estimates to SSA combined OASI and SSDI solvency in year 2031

| Solvency Measure | Our Estimates | | | Social Security Administration | | |
|----------------------------------|--------------------|-----------------------------|--------------------|--------------------------------|----------------|--------|
| | Lower ^a | Point Estimate ^a | Upper ^a | Lower | Point Estimate | Upper |
| Annual Balance ^b | -226.20 | -216.61 | -197.42 | -172.18 | -128.25 | -92.90 |
| Trust Fund Balance ^c | 1.79 | 1.87 | 2.00 | 2.42 | 2.67 | 2.87 |
| Cost Rate ^d | 17.53 | 17.70 | 17.79 | 16.71 | 17.05 | 17.49 |
| Expenditures to GDP ^d | 6.63 | 6.70 | 6.73 | 6.32 | 6.45 | 6.61 |
| Income to GDP ^d | 5.00 | 5.01 | 5.01 | 4.99 | 4.99 | 5.00 |

^a Based on uncertainty from model specification (e.g., choice of Bayesian priors)

^b Billion dollars, adjusted for inflation

^c Trillion dollars, adjusted for inflation

^d Percentage

Trust Fund Balance

As discussed earlier, the SSA increased OASI and SSDI payroll taxes in 1983 to build considerable surplus funds in preparation for an aging population. The excess revenue, held in interest-bearing Treasury bonds, had grown to \$1.8 trillion for the OASI Trust Fund and \$0.20 trillion for the SSDI Trust Fund in 2006. We estimate considerably smaller OASI and SSDI Trust Funds than does the SSA (Fig. 7, upper-right panel). We forecast steady gains in combined trust fund balance until a peak in the year 2020 between \$3.43 and \$3.47 trillion. The combined trust fund balance then declines. By 2031, we estimate it will decrease beyond its 2006 level and equal between \$1.79 and \$2.00 trillion. Under SSA projections, the combined trust fund balance is projected to increase until 2022 to between \$3.68 and \$3.75 trillion. The subsequent decline is much less pronounced. By 2031, the SSA combined trust fund balance is projected to be between \$2.42 and \$2.87 trillion, based on its intermediate-cost assumptions (see Table 2).

Cost Rate

The cost rate is the ratio of OASI and SSDI program costs to taxable payroll. We forecast an increase in the combined OASI and SSDI program costs, as a percentage of taxable payroll, from 11.11% in 2006 to between 17.53% and 17.79% in 2031 (Fig. 7, lower-left panel). In comparison, the increase is projected to be less under the SSA assumptions and to equal between 16.71% and 17.49% in 2031 (see Table 2).

Annual Income and Cost

An additional way to measure future solvency is to compare payroll tax revenue and program costs as a share of U.S. economic output. Annual payroll tax revenues vary little between mortality forecasts (Fig. 7, lower-right panel). Yet we estimate combined OASI and SSDI program costs, as a share of GDP, will rise to between 6.63%

and 6.73% in 2031, compared with between 6.32% and 6.61% under the SSA projections (see Table 2).

Balanced Budget Payroll Tax

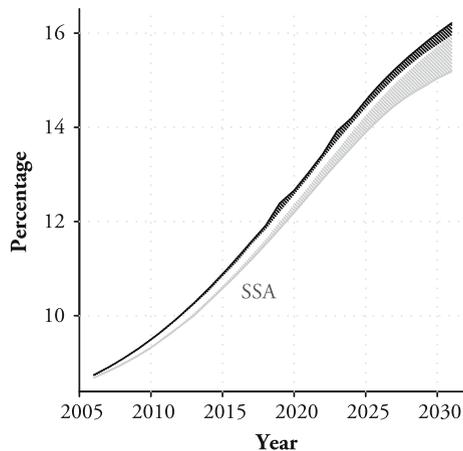
The balanced budget payroll tax rate is the tax rate required to offset annual benefit payments with the revenue generated from payroll taxes and interest from the trust fund (Lee and Tuljapurkar 1997). Although it has never been proposed to address future deficits, the balanced budget payroll tax rate is useful in assessing the effect of different mortality forecasts on Social Security finances (Lee and Skinner 1999; Lee and Tuljapurkar 1997). We calculate the 2006–2031 balanced budget payroll tax rates for both the OASI and SSDI programs under our mortality forecasts, as well as the SSA forecasts, as shown in Fig. 8.

A balanced budget provision hypothetically imposed in 2006 for the OASI and SSDI programs would, by definition, preserve solvency at 2006 levels, less loss from inflation. Initially, the combined OASI and SSDI balanced budget payroll tax rate would be much lower than the current total tax rate of 12.4% because of the surplus discussed previously. We estimate that the combined OASI and SSDI balanced budget payroll tax rate would exceed the current payroll tax rate in 2020. By 2031, the combined balanced budget payroll tax rate would be between 15.96% and 16.21%. In comparison, under SSA projections, the combined balanced budget payroll tax rate would exceed the current payroll tax rate in 2021 and would rise to only between 15.19% and 15.94% in 2030. This difference represents an additional \$31.9 to \$45.6 billion to be generated from payroll taxes. Higher payroll taxes may present a significant burden to future workers and their employers who split the contribution, and especially to the self-employed, who must contribute the full tax themselves.

Concluding Remarks

Demographic shifts in the twentieth century are at the heart of current concerns over Social Security solvency. Indeed, uncertainty in demographic processes (e.g., fertility

Fig. 8 Balanced budget payroll tax. Payroll tax required to annually balance the OASI and SSDI program budgets under our forecasts (solid lines) and SSA forecasts (grey lines)



and mortality) becomes an increasingly important component in the uncertainty of Social Security Trust Fund balances over time (Lee and Tuljapurkar 1998). We apply Bayesian methodology, which emphasizes the empirical smoothness in age-specific mortality and utilizes potentially informative covariates, to improve the quality and accuracy of SSA all-cause and cause-specific mortality forecasts. We also describe many more details of the procedures the SSA uses to forecast the long-term financial viability of the Social Security program than previously available in the public domain. This information will make it possible for researchers to evaluate the sensitivity of each of the SSA's assumptions and ultimately to marshal the power of the academic community to help ensure the future of America's largest governmental program.

The specific assumptions we focused on in this article concern one of the largest components of uncertainty—namely, age- and sex-specific mortality forecasts. We attempt to improve the accuracy and quality of mortality forecasts by introducing new methods that directly and transparently incorporate risk factors with known and emerging biological consequences and maintain long-standing demographic patterns, so long as they are consistent with the data, and emphasize the smoothness in age-specific mortality rates. Uncertainty resulting from model dependence in analyzing mortality data is reflected in our forecast intervals. We predict higher life expectancy and an older age distribution of death, when considering the steady decline in smoking and rapid rise in obesity, than do the SSA projections, which use no covariates except implicitly. The result indicates that Social Security, especially the OASI program, may be in a considerably more precarious position than officially thought. Maintaining the same set of assumptions regarding future economic and demographic growth, and changing only the mortality forecasts to more informed methods, we predict three fewer years of net surplus, \$730 billion less in the OASI and SSDI Trust Funds, program costs 0.66% greater of projected taxable payroll, and expenditures 0.25% greater of projected GDP by 2031.

Recently, Olshansky et al. (2009) reached a similar set of demographic and policy conclusions by using a cohort-components methodology. Analysis performed by the 2007 Technical Panel of Assumptions and Methods, Social Security Advisory Board, found similar solvency results based on its recommended mortality projections. When considering the impact of revised and more realistic immigration assumptions, finances of the system improved (SSABTP 2007). Our findings, and those of Lee and Tuljapurkar (1997), SSABTP (2007), and Olshansky et al. (2009), emphasize the importance of continual assessment of projection methods, underscore the need to introduce more rigorous tools and techniques, and argue for greater study on the complex interrelationship of demographic, economic, and policy processes.

We encourage other academic and government researchers to use the information we provide about SSA's methods and our models, data, methods, and software to suggest further improvements in these forecasts. Our mortality forecasting methods make it easy to systematically alter prior beliefs about demographic patterns. They also make including additional covariates based on other risk factors straightforward, when they become available. Although we include time as a simple proxy for technological change, other more specific measures may be relevant, including large-scale public health initiatives, medical advancements in detection and treatment, and pharmaceutical breakthroughs. Alternative modeling specifications are also

easy to implement in our proposed forecasting framework, as are other components of uncertainty. With all these tools, we hope the scholarly research community will find forecasting more feasible and continue to reduce uncertainty and improve the quality, accuracy, and transparency of Social Security Trust Fund projections.

Acknowledgments We thank Robert Aronowitz, Jon Bischof, David Asch, Federico Girosi, David Grande, James Greiner, Kosuke Imai, Valerie Lewis, Scott Lynch, Doug Massey, John Sabelhaus, three anonymous reviewers, and a Deputy Editor for helpful comments and suggestions; Felicitie Bell, Michael Morris, Alice Wade, and John Wilmoth for help reconstructing current Social Security Administration forecast procedures; Martin Holmer for modifying his Social Security simulation program, SSASIM, so that we could measure the effects of alternative mortality forecasts; and the Robert Wood Johnson Foundation Health & Society Scholars program, the National Institute of Child Health and Human Development (NIH 5T32 HD07163), the National Cancer Institute (RC2CA148259) and Harvard's Institute for Quantitative Social Science for research support. Earlier versions of this article were presented at the 2008 Population Association of America annual meeting and at the Harvard Center for Population and Development.

References

- Adams, K., Schatzkin, A., Harris, T., Kipnis, V., Mouw, T., Ballard-Barbash, R., & Leitzmann, M. (2006). Overweight, obesity, and mortality in a large prospective cohort of persons 50 to 71 years old. *The New England Journal of Medicine*, 355, 763–778.
- Alho, J. M. (1992). Comment on “Modeling and forecasting U.S. mortality” by R. Lee and L. Carter. *Journal of the American Statistical Association*, 87, 673–674.
- Alho, J. M., & Spencer, B. D. (1990). Effects of targets and aggregation on the propagation of error in mortality forecasts. *Mathematical Population Studies*, 2, 209–227.
- Ayres, I. (2008). *Super crunchers: Why thinking-by-numbers is the new way to be smart*. New York: Bantam Dell.
- Ball, R. (1973). *Hearings before the Special Committee on Aging* (Technical Report Part 1). U.S. Senate, 93rd Congress. SUDOC:Y4.Ag4:So1/2/pt.1.
- Bell, F. C., & Miller, M. L. (2005). *Life tables for the United States Social Security area 1900–2100* (Actuarial Study No. 120). Washington, DC: Social Security Administration, Office of the Chief Actuary.
- The Board of Trustees, Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds (TBOT). (2006). *The 2006 annual report of the Board of Trustees of the Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds* (Technical report). Washington, DC: Social Security Administration.
- The Board of Trustees, Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds (TBOT). (2007). *The 2007 annual report of the Board of Trustees of the Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds* (Technical report). Washington, DC: Social Security Administration.
- The Board of Trustees, Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds (TBOT). (2008). *The 2008 annual report of the Board of Trustees of the Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds* (Technical report). Washington, DC: Social Security Administration.
- Bongaarts, J., & Feeney, G. (2003). Estimating mean lifetime. *Proceedings of the National Academy of Sciences*, 100, 13127–13133.
- Boyer, C. (1947). Note on an early graph of statistical data (Huygens 1669). *Isis*, 37, 148–149.
- Burdick, C., & Manchester, J. (2003). *Stochastic models of the Social Security Trust Funds* (Research and Statistics Note 2003–01). Washington, DC: Division of Economic Research, Social Security Administration.
- Burns, P., Gough, S., & Bradbury, A. (2003). Management of peripheral arterial disease in primary care. *British Medical Journal*, 326, 584–588.
- Cawley, J. (2004). The impact of obesity on wages. *Journal of Human Resources*, 39, 451–474.

- Chaplain, C., & Wade, A. (2005). *Estimated OASDI long-range financial effects of several provisions requested by the Social Security Advisory Board* (Technical report). Washington, DC: Social Security Administration. Retrieved from <http://www.ssa.gov/OACT/solvency/provisions/index.html>
- Cheng, A., Miller, M., Morris, M., Schultz, J., Skirvin, J. P., & Walder, D. (2004). *A stochastic model of the long-range financial status of the OASDI program* (Actuarial Study No. 117). Washington, DC: Office of the Chief Actuary, Social Security Administration.
- Congressional Budget Office (CBO). (2001). *Uncertainty in Social Security's long-term finances: A stochastic analysis* (Technical report). Washington, DC: CBO.
- Dawes, R. M., Faust, D., & Meehl, P. E. (1989). Clinical versus actuarial judgment. *Science*, *243*, 1668–1674.
- Doll, R., Peto, R., Boreham, J., & Sutherland, I. (2004). Mortality in relation to smoking: 50 years' observations on male British doctors. *British Medical Journal*, *328*, 1519–1527.
- Doll, R., Peto, R., Wheatley, K., Gray, R., & Sutherland, I. (1994). Mortality in relation to smoking: 40 years' observations on male British doctors. *British Medical Journal*, *309*, 901–911.
- Flegal, K., Graubard, B., Williamson, D., & Gail, M. (2007). Cause-specific excess deaths associated with underweight, overweight, and obesity. *Journal of the American Medical Association*, *298*, 2028–2037.
- Girosi, F., & King, G. (2008). *Demographic forecasting*. Princeton, NJ: Princeton University Press. Retrieved from <http://gking.harvard.edu/files/smooth/>
- Gompertz, B. (1825). On the nature of the function expressive of the law of mortality. *Philosophical Transactions*, *27*, 513–585.
- Graunt, J. (1662). *Natural and political observations mentioned in a following index, and made upon the bills of mortality*. London, UK: John Martyn and James Allestry.
- Gravelle, J. G. (1998). *The proposed tobacco settlement: Who pays for the health costs of smoking?* (Technical Report 97–1053 E). Washington, DC: Congressional Research Service, Library of Congress.
- Grove, W. M. (2005). Clinical versus statistical prediction: The contribution of Paul E. Meehl. *Journal of Clinical Psychology*, *61*, 1233–1243.
- Guillot, M. (2003). The cross-sectional average length of life (CAL): A cross-sectional mortality measure that reflects the experience of cohorts. *Population Studies*, *57*, 41–54.
- Guterman, S. (2008). *Human behavior: An impediment to future mortality improvement, a focus on obesity and related matters* (Technical report, Society of Actuaries. Living to 100 and Beyond Symposium).
- Halley, E. (1693). An estimate of the degrees of mortality of mankind, drawn from curious tables of the births and funerals at the city of Breslaw; with an attempt to ascertain the price of annuities upon lives. *Philosophical Transactions of the Royal Society of London*, *17*, 596–610.
- Holmer, M. R. (2003). *Methods for stochastic trust fund projection* (Technical report). Washington, DC: Policy Simulation Group.
- Holmer, M. R. (2008). *SSASIM Guide* (Technical report). Washington, DC: Policy Simulation Group.
- Keyfitz, N. (1982). Choice of function for mortality analysis: Effective forecasting depends on a minimum parameter representation. *Theoretical Population Biology*, *21*, 239–252.
- King, G., & Soneji, S. (2011a). The future of death in America. *Demographic Research*, *25*, article 1, 1–38. doi:10.4054/DemRes.2011.25.1
- King, G., & Soneji, S. (2011b). Replication data for: The future of death in America. IQSS Dataverse Network. (Version V7). <http://hdl.handle.net/1902.1/16178>
- King, G., & Zeng, L. (2006). The dangers of extreme counterfactuals. *Political Analysis*, *14*, 131–159. Retrieved from <http://gking.harvard.edu/files/abs/counterft-abs.shtml>
- Lee, R. D., Anderson, M. W., & Tuljapurkar, S. (2003). *Stochastic forecasts of the Social Security Trust Fund*. Berkeley, CA: Center for the Economics and Demography of Aging.
- Lee, R. D., & Carter, L. R. (1992). Modeling and forecasting U.S. mortality. *Journal of the American Statistical Association*, *87*, 659–675.
- Lee, R. D., & Miller, T. (2001). Evaluating the performance of the Lee-Carter approach to modeling and forecasting mortality. *Demography*, *38*, 537–549.
- Lee, R. D., & Skinner, J. (1999). Will aging baby boomers bust the federal budget? *Journal of Economic Perspectives*, *13*, 117–140.
- Lee, R., & Tuljapurkar, S. (1997). Death and taxes: Longer life, consumption, and Social Security. *Demography*, *34*, 67–81.
- Lee, R. D., & Tuljapurkar, S. (1998). Uncertain demographic futures and Social Security finances. *American Economic Review*, *88*, 237–241.
- Levine, P., Gustafson, T., & Velenchik, A. (1997). More bad news for smokers? The effects of cigarette smoking on wages. *Industrial & Labor Relations Review*, *50*, 493–509.
- McNown, R. (1992). Comment. *Journal of the American Statistical Association*, *87*, 671–672.

- Meehl, P. E. (1954). *Clinical versus statistical prediction: A theoretical analysis and a review of the evidence*. Minneapolis: University of Minnesota Press.
- Meyerson, N., & Sabelhaus, J. (2000). Uncertainty in Social Security Trust Fund projections. *National Tax Journal*, 53, 515–529.
- Morera, O., & Dawes, R. (2006). Clinical and statistical prediction after 50 years: A dedication to Paul Meehl. *Journal of Behavioral Decision Making*, 19, 409–412.
- Olshansky, S. J. (1988). On forecasting mortality. *The Milbank Quarterly*, 66, 482–530.
- Olshansky, S. J., Goldman, D., Zheng, Y., & Rowe, J. (2009). Aging in America in the twenty-first century: Demographic forecasts from the MacArthur Foundation Research Network on an aging society. *The Milbank Quarterly*, 87, 842–862.
- Peace, L. R. (1985). A time correlation between cigarette smoking and lung cancer. *The Statistician*, 34, 371–381.
- Preston, S., & Wang, H. (2006). Sex mortality differences in the United States: The role of cohort smoking patterns. *Demography*, 43, 631–646.
- Reichmuth, W., & Sarferaz, S. (2008). *Bayesian demographic modeling and forecasting: An application to U.S. mortality* (Discussion Paper 2008–052). Berlin, Germany: Humboldt University.
- Reuser, M., Bonneux, L., & Willekens, F. (2008). The burden of mortality of obesity at middle and old age is small. A life table analysis of the US Health and Retirement Survey. *European Journal of Epidemiology*, 23, 601–607.
- Romig, K. (2008). *Social Security: What would happen if the trust funds ran out?* (Technical Report RL33514). Washington, DC: Congressional Research Service.
- Ryan, J., Zwerling, C., & Orav, E. J. (1992). Occupational risks associated with cigarette smoking: A prospective study. *American Journal of Public Health*, 82, 29–32.
- Schneider, E. (1999). Aging in the third millennium. *Science*, 283, 796–797.
- Sloan, F., Ostermann, J., Picone, G., Conover, C., & Taylor, D. (2004). *The price of smoking*. Cambridge, MA: The MIT Press.
- Social Security Administration Historian's Office. (2007). *Social Security A brief history* (Technical Report 21–059). Washington, DC: Social Security Administration.
- Social Security Administration Historian's Office. (2010). *Historical background and development of Social Security* (Technical report). Washington, DC: Social Security Administration. Retrieved from <http://www.ssa.gov/history>
- Social Security Advisory Board Technical Panel (SSABTP). (1991). *1991 Technical Panel on Assumptions and Methods* (Technical report). Washington, DC: Social Security Advisory Board.
- Social Security Advisory Board Technical Panel (SSABTP). (1994). *1994 Technical Panel on Assumptions and Methods* (Technical report). Washington, DC: Social Security Advisory Board.
- Social Security Advisory Board Technical Panel (SSABTP). (1999). *1999 Technical Panel on Assumptions and Methods* (Technical report). Washington, DC: Social Security Advisory Board.
- Social Security Advisory Board Technical Panel (SSABTP). (2007). *2007 Technical Panel on Assumptions and Methods* (Technical report). Washington, DC: Social Security Advisory Board.
- Stewart, S. T., Cutler, D. M., & Rosen, A. B. (2009). Forecasting the effects of obesity and smoking on US life expectancy. *The New England Journal of Medicine*, 361, 2252–2260.
- Sturm, R. (2002). The effects of obesity, smoking, and drinking on medical problems and cost. *Health Affairs*, 21, 245–253.
- Suk, S.-H., Sacco, R., Boden-Albala, B., Cheun, J., Pittman, J., Elkind, M., & Paik, M. (2003). Abdominal obesity and the risk of ischemic stroke: The Northern Manhattan Stroke Study. *Stroke*, 34, 1586–1592.
- Swendiman, K., & Nicola, T. (2008). *Social Security reform: Legal analysis of Social Security benefit entitlement issues* (Technical Report RL32822). Washington, DC: Congressional Research Service.
- Thorpe, R. M., & Ferraro, K. F. (2004). Aging, obesity, and mortality: misplaced concern about obese older people??. *Research on Aging*, 26, 108–129.
- United States Government. (2009). *Budget of the United States Government, Fiscal Year 2009* (Technical report). Washington, DC: US Government Printing Office.
- Vollgraff, J. A. (Ed.). (1950). *Oeuvres complètes de Christiaan Huygens. Publiées par la Société hollandaise des sciences [Complete Works of Christiaan Huygens. Published by the Dutch Society of Sciences]*. The Hague, The Netherlands: M. Nijhoff.
- Wade, A. (2010). Mortality projections for Social Security programs in the United States. *North American Actuarial Journal*, 14, 299–315.
- Wang, H., & Preston, S. (2009). Forecasting United States mortality using cohort smoking histories. *Proceedings of the National Academy of Sciences*, 109, 393–398.

- Wilmoth, J. R. (1995). Are mortality projections always more pessimistic when disaggregated by cause of death? *Mathematical Population Studies*, *5*, 293–319.
- Wilmoth, J. R. (2003). *Overview and discussion of the Social Security mortality projections* (Technical report Technical Panel on Assumptions and Methods). Washington, DC: Social Security Advisory Board.
- Wilmoth, J. R. (2005a). On the relationship between period and cohort mortality. *Demographic Research*, *13*, article 11, 231–280. doi:[10.4054/DemRes.2005.13.11](https://doi.org/10.4054/DemRes.2005.13.11)
- Wilmoth, J. R. (2005b). Some methodological issues in mortality projection, based on an analysis of the US Social Security system. *Genus*, *61*, 179–211.
- Wolf, P. A., D'Agostino, R. B., Kannel, W. B., Bonita, R., & Belanger, A. J. (1998). Cigarette smoking as a risk factor for stroke. The Framingham Study. *Journal of the American Medical Association*, *259*, 1025–1029.