A Primer on
Modeling Income in the Near Term, Version 7
(MINT7)

by

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ABSTRACT

Modeling Income in the Near Term (MINT) is a dynamic microsimulation model developed by the Social Security Administration to facilitate analysis of proposals to change Social Security benefits and payroll taxes. This primer describes MINT's development history. It then details the model's starting sample and the specification of its demographic and economic aging modules, including the calculators that compute various benefits and taxes. It also provides information about previous analyses that have relied on MINT.

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ACRONYMS

ACA	Affordable Care Act
AMT	Alternative Minimum Tax
CB	Cash Balance
CBO	Congressional Budget Office
CBOLT	Congressional Budget Office Long-Term dynamic microsimulation model
DB	Defined Benefit
DC	Defined Contribution
DER	Detailed Earnings Record
DI	Disability Insurance
DOMA	Defense of Marriage Act
DPE	Division of Policy Evaluation
DYNASIM	Dynamic Simulation of Income Model
EBRI	Employee Benefits Research Institute
FPL	Federal Poverty Level
GPO	Government Pension Offset
HRS	Health and Retirement Study
ISM	In-Kind Support and Maintenance
IRS	Internal Revenue Service
MBR	Master Beneficiary Record
MEPS	Medical Expenditures Panel Survey
MINT	Modeling Income in the Near Term
NBER	National Bureau of Economic Research
OACT	Office of the Chief Actuary
OASDI	Old-Age, Survivors, and Disability Insurance
OASI	Old-Age and Survivors Insurance
OLS	Ordinary Least Squares
ORES	Office of Research, Evaluation, and Statistics
ORP	Office of Retirement Policy
PBGC	Pension Benefit Guaranty Corporation
PIA	Primary Insurance Amount
PIMS	Pension Insurance Modeling System
PSID	Panel Study of Income Dynamics
POLISIM	Policy Simulation Model
RET	Retirement Earnings Test
SCF	Survey of Consumer Finances
SER	Summary Earnings Record
SIPP	Survey of Income and Program Participation
SNAP	Supplemental Nutrition Assistance Program
SOI	Statistics of Income
SPM	Supplemental Poverty Measure
SSA	Social Security Administration
SSI	Supplemental Security Income
SSR	Supplemental Security Record

TANF	Temporary Assistance for Needy Families
TDI	Temporary Disability Insurance
TRIM	Transfer Income Model
UI	Unemployment Insurance
WEP	Windfall Elimination Provision
WIC	Women, Infants, and Children

OVERVIEW

This primer describes Modeling Income in the Near Term, Version 7 (MINT7). MINT7 is a tool developed by the Division of Policy Evaluation (DPE) of the Office of Research, Evaluation, and Statistics (ORES) of the Social Security Administration (SSA) for use throughout SSA to analyze the distributional consequences of proposals to modify the Old-Age, Survivors, and Disability Insurance (OASDI) program, better known as Social Security.[1] Contractors from the Urban Institute, the Brookings Institution, and the RAND Corporation have contributed to MINT's development. Other MINT contributors have included Jon Bakija from Williams College, John Coder of Sentier Research, Martin Holmer from Policy Simulation Group, and Douglas Wolf from Syracuse University. Over the years, several advisory boards have also provided input on MINT.[2]

We do not intend to fully document MINT in this primer.[3] Rather, we provide a broad, high-level overview and extensive citations to more comprehensive documents for those seeking additional, more detailed information on model specification. We also place MINT7 in historical context, detail published analyses that use MINT, and make recommendations for using the model effectively.

MINT7 is based on a micro-level data file of actual and projected individuals born between 1926 and 2067. It starts with a large sample of individuals from the Survey of Income and Program Participation (SIPP) with a rich set of income and demographic characteristics. Individuals in SIPP who were born prior to 1980 are linked to their SSA and other government records on earnings, benefits, and mortality.[4] MINT then projects life outcomes for these core birth cohorts—1926 through 1979—until death or the year 2099. MINT also projects life outcomes for individuals in extended cohorts—born 1980 through 2067—but using a somewhat different projection approach than for the core cohorts. The projections for the extended cohorts use a synthetic population born from 1980 to 2076 generated from the SSA's Policy Simulation Model (POLISIM) model. MINT selects individuals at age 32 and links them to similar aged SIPP respondents. This link provides a starting point for the extended cohorts that includes the

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[1] Throughout this report, we use the terms OASDI and Social Security interchangeably. When we wish to refer to a subset of Social Security, like Old-Age and Survivors Insurance (OASI) or Disability Insurance (DI), we do so explicitly.

[2] Advisors from outside SSA have included Christopher Bone, Richard Burkhauser, Alan Gustman, Mark Hayward, Kathleen McGarry, Olivia Mitchell, John Rust, John Sabelhaus, and Finis Welch. While these advisors provided valuable advice, they are not responsible for ultimate choices about model specification.

[3] See The Urban Institute (2013a) for dataset documentation.

[4] The administrative files MINT uses include the following:

-The Detailed Earnings Record (DER) and Summary Earnings Record (SER), which provide information on earnings, Social Security coverage, and contributions to deferred earnings plans, like 401(k) and 403(b) plans, plus limited demographic information, like date of birth;

-The Supplemental Security Record (SSR), which provides information on Supplemental Security Income (SSI) receipt;

-The Master Beneficiary Record (MBR), which provides information on timing, level, and type of benefits received from OASDI; and

-The Numident, which provides information on date of death and place of birth, year of entry, and legal status at entry for the foreign born.

rich histories for individuals in the core cohorts through age 31, including prior earnings, job characteristics, assets, marriage, fertility and immigration histories, and health measures. MINT7 uses various algorithms to project outcomes for each individual from the interview year until death or the year 2099.[5]

While MINT starts with the SIPP data, it relies on data sources other than SIPP when projecting some outcomes, based on the rationale that any function should use the best available data.[6] These sources include the Health and Retirement Study (HRS), Panel Study of Income Dynamics (PSID), Survey of Consumer Finances (SCF), and Medical Expenditures Panel Survey (MEPS). MINT7 calibrates many key outcomes to the 2012 Social Security Trustees' intermediate assumptions (OASDI Board of Trustees 2012). Calibrated outcomes include future price and wage growth and key Social Security benefit formula parameters.[7] Demographic outcomes in MINT, such as Disability Insurance (DI) benefit receipt, life expectancy, and net immigration, are also tied to the Trustees' intermediate assumptions.

DYNAMIC MICROSIMULATION

MINT is a microsimulation model. The microsimulation modeling strategy was first conceptualized by Guy Orcutt (1957). Orcutt's vision is that bottom-up representations of economic and demographic processes, combined with detailed representations of program rules, can inform policy by revealing interactions and trends that more aggregate analyses may fail to capture.

Microsimulation models can be either *static* or *dynamic*. Static microsimulation models typically simulate the immediate effects of a change in law or policy on the current population. Dynamic simulation models simulate the effects of changes in law or policy on a population over time, sometimes over very extended horizons. MINT falls into the latter category. Either type of model may or may not simulate behavioral responses that might result from changes in law or policy.

HISTORY OF MINT

MINT is based on the "past is prologue" approach Iams and Sandell (1997) outlined. Table 1 provides a succinct history of MINT's development, with references to model documentation and analyses. As the table indicates, MINT1 was produced by analysts from the Urban Institute, the Brookings Institution, and the RAND Corporation and is described in Toder et al. (1999) and

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[5] While developing MINT, we experimented with different donor ages for the extended cohorts. The advantage to using an earlier age is that MINT can readily forecast Disability Insurance (DI) receipt at younger ages. The advantage to using a later age is that formal education is less likely to be incomplete (be "right censored" in statistical terms), an important limitation given education's central role in predicting earnings and given that MINT does not currently model education.
[6] While we use SIPP for estimating parameters in many MINT functions, in some cases the SIPP data are too limited to enable estimation. For example, the relatively short SIPP panels may not be adequate for estimating random effects models, and information about defined benefit pension accruals is insufficient for developing a detailed retirement decision model. Some interesting outcome data are only available in a single topical module of the SIPP, making it impossible to estimate transitions or other types of dynamics.
[7] While the Trustees' assumptions inform MINT employment rates, the model does not directly calibrate to them.

Panis and Lillard (1999). Analysts from the Urban Institute again collaborated with Brookings Institution researchers for MINT3, described in Toder et al. (2002). Analysts from the Urban Institute developed subsequent versions of MINT. MINT4, MINT5, MINT6, and MINT7 are described, respectively, in Smith et al. (2005), Smith et al. (2007), Smith et al. (2010), and Smith and Favreault (2013). A number of articles and working papers, including several published in the *Social Security Bulletin*, have also described MINT findings and methods (see last column of table 1).

Each subsequent version of MINT has enhanced the earlier version by adding more recent data, updating assumptions, refining the projection methods, and expanding the suite of modeled outcomes and sample cohorts.

Published and Publicly Available Policy Analyses Using MINT

MINT is widely used to provide distributional forecasts of changes to Social Security. For example, MINT projections are used in the National Commission on Fiscal Responsibility and Reform report (2010; see Figure 13, page 55). Analysts from SSA's Office of Retirement Policy (ORP) further provide the public with results from MINT through SSA's Web site, for example, which includes analyses for prominent provisions to change Social Security (SSA 2011).[8,9] Researchers from various Social Security offices have also used MINT projections in published articles about proposals to change Social Security that have appeared in academic journals and similar venues (for example, Iams, Reznik, and Tamborini 2010; Olsen and Romig 2013; Reznik, Weaver, and Biggs 2009; Shoffner 2010; and Tamborini and Whitman 2008, 2010). MINT is also frequently used for policy briefs (for example, Olsen 2008; Sarney 2008, 2010; and Springstead 2010, 2011), even by researchers outside SSA (Reno and Walker 2011). Researchers from the United States General Accounting Office have also used MINT in several analyses (2001, 2004).

MINT in the Context of Other Microsimulation Models

MINT draws on techniques, data, and parameters that other US-based dynamic microsimulation models have used. For example, the targets for MINT's extended cohorts are derived from the POLISIM model, housed in SSA's Office of the Chief Actuary (OACT). Similarly, MINT's job change model, a component of the pension projection module, uses age-centered regression techniques developed by analysts from the Congressional Budget Office (CBO) (Sabelhaus and Walker 2009). MINT's pension model draws on other, related research (Sabelhaus and Brady 2008). MINT shares substantial numbers of functions with the Dynamic Simulation of Income Model (DYNASIM), developed by the Urban Institute. MINT also uses parameters from a static

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[8] The group historically has not provided cost analyses. The Office of the Chief Actuary provides such estimates on its web site, and the Congressional Budget Office (CBO) periodically releases similar projections (for example, CBO 2012).

[9] These distributional analyses use a wide range of cross-sectional outcome measures, including medians of both individual Social Security benefits and household total income. MINT tables present the percentages of beneficiaries changes affect, while special tabulations provide projections of the sizes of changes among those a policy change affects. Analysts often juxtapose the cross-sectional simulation results at three points in time: 2030, 2050, and 2070. Various tables classify individuals by gender, education, household income, lifetime earnings, payable lifetime earnings, marital status, race, and type of benefit (retired worker, survivor, disabled worker, spouse, dually entitled survivor, dually entitled spouse). Some MINT analyses include projections of poverty status.

microsimulation model, the Urban Institute's Transfer Income Model (TRIM). These synergies help to enhance MINT's validity efficiently, given the considerable development costs for such complex, data-intensive, and detailed models.

WHY START THE SIMULATION IN 2004 THROUGH 2011?

MINT7 starts with data from the 2004 and 2008 SIPP panels matched to administrative data through 2010. MINT7 projects the elements in the administrative data after 2010. With some exceptions, projections for items observed in the SIPP start after the last SIPP-based observation, usually in 2005 or 2009 for the respective panels. One philosophy behind MINT's design is that capturing correlations between complex processes is extremely difficult, and using the most recent data with a minimum of imputation helps to ensure validity. Because so many life history elements are available in the administrative data and the SIPP topical modules, the amount of baseline imputation required in MINT is relatively modest. The Congressional Budget Office long-term dynamic microsimulation model (CBOLT) similarly starts with a recent baseline.

Some other dynamic microsimulation models start in a more distant historical period. For example, POLISIM and its predecessor Corsim started in 1980 and 1960, respectively, and DYNASIM starts with a baseline sample set in 1992. The rationale for these comparatively early start dates is that they enable developers to validate the projections over the historical period.[10] Similarly, developers can also align outcomes and determine whether any patterns in the alignment factors indicate changing processes or flawed specification.[11] MINT7 uses only minimal alignment in its aging algorithms. Models that start earlier also allow comparisons of past, current, and future time periods. Individuals who did not survive to provide SIPP interviews, either through death or emigration, are not included in the MINT7 sample.

STARTING SAMPLE AND EARNINGS AND MARRIAGE HISTORY DATA

STARTING SAMPLES: BASE, EXTENDED COHORT SAMPLE, AND IMMIGRANT FILE

The initial MINT7 file contains 82,782 observations, 45,214 from the 2004 panel and 37,568 from 2008 panel (table 2), for individuals born from 1926 through 1979. For individuals in these core cohorts, MINT uses data from a key set of topical modules collected in waves 1 through 7 of the SIPP panels. Only individuals with a positive wave 7 longitudinal panel weight are included in the sample.[12] Weights are based on SIPP weights, with small adjustments to account for high levels of mortality in the DI population, especially around the time of first receipt. Without such adjustments, MINT might understate the number of short-duration DI beneficiaries.

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[10] To some degree, they also reflect aging of the models themselves. For example, DYNASIM's starting sample was among the most recent available at the time the current version of the model was developed. Irregular updating may reflect responses to developer priorities and resource constraints.

[11] For more information about alignment in dynamic microsimulation models, see, for example, Klevmarken (1998) and Neufeld (2000).

[12] MINT uses data from the following topical modules: employment history; marriage history; fertility history; migration history; disability history; health conditions and work limitations; retirement and pension plan coverage; assets and liabilities; annual income and retirement accounts; and employer-provided health benefits.

To project individuals born after 1979, MINT adds the extended cohorts based on POLISIM projections.[13] These cohorts total 210,712 people. MINT also adds 34,295 immigrants who are projected to arrive after the SIPP baseline. In sum this yields a final MINT7 file with 327,789 observations.

The unit of analysis for MINT is the individual. However, MINT tracks marital histories for each person on the file. This enables MINT users to calculate both couple and individual income and assets and to use spouses' characteristics in several of the model's aging functions.

EARNINGS AND MARRIAGE/FERTILITY HISTORIES

Because Social Security benefits depend both on one's own lifetime earnings and on one's marital experience and spouses' lifetime earnings, MINT's starting sample is enriched with earnings and marital histories. Fortunately, administrative records and SIPP topical module data can provide this information.[14] For individuals with a match to the administrative records, we observe OASDI-covered earnings from 1951 through 2010 and total earnings from 1983 through 2010.[15] About 87 percent of respondents matched to earnings records in the 2004 panel and 93 percent matched in the 2008 panel (table 2).[16] For individuals not matched to the administrative earnings data, MINT uses a hotdecking approach to find a similar person and then uses that person's earnings history as a proxy for the non-matched SIPP respondent's earnings and benefit history to date. The matching variables include age, sex, DI status, SSI beneficiary indicator, self-reported defined contribution (DC) plan status (yes, no, missing), average monthly earnings, age of immigration, immigrant source region (native, developed, undeveloped), number of years worked in last 10 years, education, race, and class of worker (government, private, none).

Marriage and fertility history data are collected in topical module 2. These data include information on the number of times married, the start and end dates for first and last marriages, the number of children ever born, and the birth dates for the first and last children born.[17] MINT uses the core data to fill in birth dates for observed children in the household. It imputes marriage start and end dates for respondents reporting more than two prior marriages.

[13] We elected to use POLISIM because the model is calibrated to intermediate assumptions from the Social Security Trustees' Report (OASDI Board of Trustees 2012) and has information about individuals' education, nativity (and region of origin for the foreign born), race, and marital status. We use these characteristics to select an appropriate mix of records from the SIPP sample for the later cohorts. For information about an earlier version of POLISIM, see Favreault and Smith (2007).
[14] MINT ignores administrative data when the difference in SIPP self-reported birth year and administrative birth year is more than five years. MINT treats these records as non-matched cases and imputes the administrative data values for these respondents.
[15] While total earnings are available from as early as 1978, the data are not high quality until about 1983.
[16] Table 2 also reports match rates to Numident, which are comparable to the SER match rates, and to benefit records for OASDI and SSI (the MBR and SSR, respectively). The rates for the benefit records are much lower than for the earnings and mortality records because they may not be established until one makes a claim for benefits. Several researchers have examined match representativeness for SIPP (for example, Davis and Mazumder 2011).
[17] Since the 2001 panel, some of these data fields have been restricted, but SSA has obtained the required permissions to use these detailed data.

Aging Modules and Sequence

Given this enriched starting sample, MINT ages the population, projecting key variables using a variety of techniques, including regression models, statistical matching, and rule-based algorithms. Figure 1 shows a simplified representation of MINT's aging sequence (for a more detailed representation, see Urban Institute 2013b, pages 8–9). Tables 3 through 6 provide summary information about MINT's projection algorithms for demographics (table 3); disability, employment, and earnings (table 4); employer-provided pensions (table 5); wealth (table 6); and, finally, other income sources and expenditures (table 7). We next detail these components.[18]

Family Demographics: Marriage, Divorce, and Spouse Characteristics

The projections of marriage and divorce after baseline are among the first that MINT makes. These projections, based on continuous time hazard models, cover an individual's lifetime. These models take into account age and cohort effects as well as important socioeconomic differentials (e.g., race, education, income) and important duration effects (e.g., how long one has been married or unmarried) in assigning the likelihood of marrying or divorcing. One limitation is that disability is not incorporated as well as it could be in these functions.

Once MINT has projected that an individual gets married, MINT matches him or her to a spouse. This match is made based on age, projected marriage begin and end dates, education, race/ethnicity, disability status, and lifetime earnings (Smith, Scheuren, and Berk 2002).[19] An important characteristic of MINT's marriage matching algorithms is that an individual can be matched to multiple spouses. This is known as an "open" marriage market.[20] Essentially, the spouse match provides the economic and demographic characteristics for each spouse over the respondent's lifetime.

MINT does not currently model same-sex marriage. Developers made this simplifying assumption before the Supreme Court ruled the Defense of Marriage Act (DOMA) unconstitutional, opening the door for same-sex couples to receive spouse and survivor benefits from OASDI. Correspondingly, SSA may wish to revisit this area in the future.

Family Demographics: Immigration and Emigration

MINT uses immigrants who were sampled in the SIPP data as "donors" to provide starting characteristics for future immigrants. The numbers of immigrants that enter the model each year are determined by the intermediate targets in the Social Security Trustees' Report by age.[21] We

[18] As we detail projection algorithms, we will highlight a few interesting aspects of each. We cannot detail all completely. Please see the tables and referenced documents for more complete descriptions.
[19] Match weights are not empirically derived, but rather assumed.
[20] A closed marriage market is one in which there is exactly one spouse for every married person in the simulation. If there are insufficient numbers of partners for the sample of individuals selected to marry in a given year, then the person does not marry that year, but can instead re-enter the marriage pool in subsequent years.
[21] Net immigration is the number of immigrants that enter the United States less the number of US residents that emigrate. MINT immigration targets require converting the net Trustees' immigrant targets into gross immigrants targets (before emigration). MINT7 uses the emigration hazard from Dowhan and Duleep (2002) to gross up the annual Trustees' net immigrants by age, sex, and year. It uses US Department of Homeland Security Yearbook data (2012a, 2012b) to impute source region and legal status to the target population.

rely on donor characteristics up through the age of arrival in the United States, but after arrival, immigrant outcomes such as earnings, marriage, divorce, mortality, and program participation, evolve in ways that reflect changes in the larger society (for example, mortality improvements, reductions in fertility, and shifts in pension coverage). Many aging algorithms include nativity indicators, as tables 3 through 6 indicate.

One simplifying assumption in MINT is that only immigrants are eligible to emigrate. Immigrants enter the model with a propensity to emigrate (an individual specific error), and this propensity declines with their time in the country.[22]

INDIVIDUAL DEMOGRAPHICS: BIRTH AND DEATH

The SIPP contains detailed data on women's fertility histories from the fertility history topical module. The model completes these histories for those who have not reached the end of their childbearing years prior to the MINT baseline using regressions based on marital status and number of children born. Men inherit the fertility history of their spouses in the years they are married, and out-of-wedlock children (based on self-reports) are imputed using estimates from out-of-wedlock births among women.

Death is modeled separately on the basis of age, sex, and disability status. At older ages, separate regression functions for men and women compute death probabilities. Explanatory variables include age, education, race, marital status indicators, and various interactions. At younger ages, death is modeled as part of the earnings and disability simulation, as the next section describes. Death rates are roughly calibrated to match the intermediate assumptions of the OASDI Trustees' Report on an age-sex-year basis.

EMPLOYMENT EARNINGS DISABILITY AND DEATH THROUGH AGE 54 (AGE 67 FOR DI BENEFICIARIES)

Because of the close correlation between earnings, death, and DI receipt, MINT models these processes jointly in prime age (through age 54 for the non-disabled and age 67 for those who ever participated in DI) using a hotdeck statistical matching algorithm. As table 4 indicates, key variables in the distance function are age, gender, DI benefit status, number of years worked out of the last five years, average earnings in last five years, work status in year 5 of the match period, work status in year 4 of match period, lifetime earnings quintile by cohort and sex, education, race/ethnicity, uncovered worker indicator, self-employed indicator, and SSI receipt. Five-year segments of these outcomes are spliced together, with "recipients" receiving data from individuals who were the age one is now turning in later years of the matched SIPP data. This maintains all the year-to-year relationships among these outcomes within the five-year imputation block. Figure 2 illustrates how the splicing algorithms work in a simplified way.[23] Donors for each cohort include respondents from eight preceding cohorts. This pooling allows MINT to smooth over recession periods and capture recent decedents. A complex calibration

[22] MINT immigrants leave as individuals, rather than as family units.
[23] In reality, the algorithm is more complex, searching throughout the donor file for an exact match on these variables, and then incrementally relaxing the match criteria until a satisfactory match is found. The match imputes earnings, disability status, and mortality information.

process involving alternate donors ensures that these projections meet OACT targets by age, sex, and year.[24]

Over the years of developing MINT, it has become clear that these earnings projections are very sensitive to the launch point (the last year of observed data before the projection algorithm takes over). Because the last year for which MINT7 had observed data (2010) was in the immediate aftermath of a severe recession,[25] we "derecessionize" the donor data.[26] This is more consistent with the Trustees' assumptions and most other long-range forecasters, which tend to average over business cycles after the relatively near term.

Health Status and Work Limitations

Beyond DI beneficiary status, MINT includes two health indicators at ages 51 and older. The first is self-reported health status, modeled from age 51 to death. While many surveys classify health using a five-point scale (excellent, very good, good, fair, poor), MINT uses a two-outcome scale (fair or poor versus other). MINT's second indicator is self-reported work limitations, which is available from ages 51 through 67, with three possible outcomes: no health condition that limits work, condition that limits but does not prevent work, and condition that prevents work. As with other MINT variables, starting values are observed from the SIPP. Because these elements are projected after mortality and DI receipt, survival and DI status are used as predictors in the equations to ensure proper correlation, along with standard demographic information like education and race (table 3 for work limitations, table 4 for health).

Earnings at Age 55 and Older

Because MINT is focused on projecting retirement income adequacy, developers elected to include a very explicit model of the retirement decision, where retirement is defined as a drop in usual weekly work hours below 20. The retirement model places special attention on retirement income replacement rates, and contains a lot of information about potential retirement resources and family situation (table 4). For those who choose not to retire in a given year, earnings after the splicing part of the model are projected using age-education fixed-effect models. For those

[24] The technique MINT7's statistical match uses to perform the calibration relies on assigning several potential donors for each recipient and performing multiple rounds of projections. If a Trustees' target is not reached in the first round of projections, then the program swaps donors to align the projections to the target disability prevalence and mortality rates (Toder et al. 2002). For example, if DI prevalence is too low, the program loops through the individuals who were not selected to become disabled and swaps a requisite number of those who have an alternate donor who is disabled to disabled status. Sometimes this requires multiple rounds, given that individuals in MINT do not have equal weights, so swapping an individual with a high weight can lead MINT to overshoot or undershoot the desired disability rate for a given age-sex group.

[25] The National Bureau of Economic Research dates the great recession as having lasted from December 2007 through June 2009. High unemployment often endures long after the recession officially ends.

[26] The de-recession process leaves the historic earnings record unaltered but replaces the donor record with an updated future that has higher employment rates. Specifically, we count up the number of years between 2006 and 2010 with zero earnings each donor record has. For 80 percent of cases with zero years, we make changes as follows: For donors with one year of zero earnings, we replace the zero year with the average of the four nonzero years. For donors with two years of zero earnings, we replace a randomly selected zero year with the average of the three nonzero earnings. For donors with three years of zero earnings, we replace a selected zero year with the average of the two nonzero earnings. We made no changes to donor earnings for disabled donors and donors age 60 and older.

who do retire, MINT uses separate regressions to forecast the probability of work and earnings among workers using covariates that reflect health status and work experience.

The process of modeling earnings at older work ages also closely accounts for beneficiary status, given policies like the Retirement Earnings Test (RET). To model beneficiary status, MINT includes a set of hazard models for Old-Age and Survivors Insurance (OASI) claiming. These models separately consider spouse-only beneficiaries, high earners, and lower earners. Once an individual has elected to claim benefits, a new set of equations projects employment and earnings based on whether one is a first-year claimant and other factors. A final set of equations models employment and earnings at age 70 and older. An innovation for MINT7 is that these equations now account for life expectancy.

PENSIONS, INCLUDING JOB CHANGE AND JOB CHARACTERISTICS

MINT tries to capture the very complex and rapidly changing US pension climate. The model starts with observed information on pension coverage from SIPP self-reports and from DER records on contributions to 401(k) and 403(b)-type pensions (“deferred earnings”). The model represents pensions from defined benefit (DB), defined contribution (DC), cash balance (CB), and combination plans.

Individuals with DB pension coverage are matched to detailed plan provisions from the Pension Insurance Modeling System (PIMS) developed by the Pension Benefit Guaranty Corporation (PBGC). This enables computation of their pension benefits once claimed. Those individuals covered by DC plans can make annual contributions, according to a two-stage process. A first equation predicts the decision to participate given an offer. A second equation predicts the amount one contributes given participation. Explanatory variables in these equations include information about employer contributions and demographic and economic characteristics (table 5).

Individuals are assigned an individual-specific risk tolerance based on a multinomial logit model estimated with Survey of Consumer Finances (SCF) data (Smith et al. 2010, chapter 5). Given an individual’s risk tolerance, retirement account balances are allocated to a mix of stocks and bonds. Individuals with higher tolerance for risk invest a larger share of assets in stocks than do individuals with lower tolerance, and asset investments shift more to bonds for all individuals with age.

Using target-date fund prevalence from the Employee Benefits Research Institute (EBRI) (Copeland 2011), MINT7 assigns 50 percent of new workers and 10 percent of SIPP baseline workers with a DC pension to select a target-date fund investment. This assignment method imputes higher initial target-date fund participation for younger workers, lower-tenure workers, and workers with lower account balances than for older, longer tenure, and higher balance account holders, consistent with EBRI tabulations (see Copeland 2011, figure 1). A rising share of workers will have target-date funds over time, as workers enter the labor market, change jobs, and increasingly have exposure to target-date fund selection.

MINT7 randomly assigns workers to a target date fund based on the dollar-weighted share of the 40 largest target date funds according to Morningstar (Morningstar 2012, table 3). MINT7 assumes that target-date fund selection is an absorbing state. Once workers are projected to select a target-date fund, they remain target-date investors until retirement. MINT7 reassigns the specific target-date fund at every job change and assumes that all accumulated DC assets are allocated based on the new target-date fund's asset mix (balances accumulated from prior employment follow the new job's target-date fund asset allocation). MINT7 rebalances target-date fund investments annually and standard investment portfolios once every five years.

Stock and bond portfolios earn stochastic rates of return centered around the historic mean stock and bond returns through 2012 and projected average returns thereafter (Ibbotson 2013). MINT7 assumes 7.4 percent real rate of return on stocks through 2017, based on a partial recovery scenario outlined by Butrica, Smith, and Toder (2010), and 6.5 percent real rate of return thereafter. Bond portfolios include 40 percent long-term government bonds and 60 percent corporate bonds. After 2012, MINT7 assumes a 3.5 percent real rate of return on corporate bonds and a 3 percent real rate of return on government bonds. Actual annual returns include individual-specific stochastic variance of 0.1728 on stocks and 0.0214 on bonds. MINT7 subtracts 1 percent from stock and bond annual returns to reflect administrative costs.

Individuals in MINT can change jobs. When they do, their job characteristics, including health insurance offer and premiums, union status, employment sector, pension coverage, and pension type—DB, DC, CB, or some combination—may also change according to an elaborate model (table 5). MINT workers may also cash out their DC pension accruals rather than rolling them over upon a job loss or job change, reducing their accumulated wealth. Younger workers, those with lower account balances, and those with job losses are more likely to cash out accumulated balances compared to older workers, those with higher account balances, and workers who seamlessly move from one job to another. When married workers claim their pensions, they decide whether to receive a joint and survivor annuity. For workers selecting a survivor annuity, the survivor receives half of the sponsor's pension benefit. All government DB pensions and a share of private-sector pensions are adjusted annually for cost of living increases.

As part of the projection process, MINT7 models continuing evolution in the pension sector. So even if a worker does not change jobs, his or her pension can still change. MINT7 models freezes in DB plans, plan conversions, and the proliferation of target date funds as options for DC plans. Specifically, the default MINT7 dataset assumes that all non-union private DB pension plans implement a hard freeze between 2007 and 2016 and two-thirds of state and local government DB plans implement a soft freeze between 2007 and 2016.

WEALTH

As with pensions, MINT7 wealth projections begin with self-reports from the relevant SIPP topical modules. Because of known deficiencies in SIPP's wealth data, MINT calibrates the initial wealth distribution to data from the SCF. MINT projects housing wealth separately from non-housing wealth. The latter concept, which we sometimes label as financial assets, includes vehicles, other real estate, and farm and business equity; stock, mutual fund, and bond values; checking, saving, money market, and certificate of deposit account balances; and value of other assets, less unsecured debt.

MINT projects wealth in several phases we can characterize simply as *build up* and *spenddown*, though the latter term is somewhat of a misnomer because a share of the elderly continues to accumulate wealth in retirement. The present value of lifetime earnings is a key predictor of wealth, which is modeled separately for unmarried and married people (table 6).

Smith, Michelmore, and Toder (2008) provide an extensive evaluation of wealth projections in an earlier version of MINT. They observe that wealth estimates in the available nationally representative data sources differ significantly from one another, making it challenging to determine precisely how well the model was performing. MINT's asset projections generally align with the target SCF historical series.

One challenge for analysts is how to convert wealth values into income streams. MINT enables the user to choose among several options, depending upon one's interest. For example, one can assume a rate of return on projected wealth. Alternatively, MINT includes two separate annuity factors that allow users to convert assets into income flows. One annuity factor is based on unisex age and cohort mortality rates from the 2012 Trustees' assumptions. The second annuity factor varies by age, sex, cohort, education, and race. The annuity factors assume a 50 percent joint and survivor annuity using a 3 percent real return on assets. MINT also imputes taxable interest, dividend, rental income, and capital gains as a function of accumulated assets based on a statistical match to the Statistics of Income (SOI) data (Smith et al. 2007, chapter 5). It also calculates annual taxable withdrawals from retirement account balances including statutory minimum distribution requirements after age 70.

Transfer Income, Including SSI and Noncash Transfers

To better capture total incomes and thus poverty status, MINT began to include SSI benefits starting in MINT3. Starting in MINT6, the model started to include other cash transfers, including means-tested sources like Temporary Assistance for Needy Families (TANF) and general assistance and non-means-tested sources like workers compensation, veterans compensation, Unemployment Insurance (UI), state-level temporary disability insurance (TDI), severance payments, employer/union temporary sickness payments, own sickness, accident, and employer disability payments. MINT7 has now added noncash transfers, including food assistance like Supplemental Nutrition Assistance Program (SNAP) and Women, Infants, and Children (WIC) and heating and rental assistance to the model.

While these transfer projections are stylized relative to a full-scale static microsimulation model like TRIM that would model most of the rules for these programs directly, they offer a great improvement over not including this information. This is especially true when examining the well-being of working-age individuals and DI beneficiaries, given that many of these sources, like TANF, tend to be concentrated outside the retiree population that was MINT's original focus.

The SSI module is the most directly rule-based of these functions. The module begins by applying an eligibility screen that mimics SSI law to all individuals in the model who are age- or disability eligible.[27] Literature shows that not all who are eligible for SSI participate in the program. So MINT uses logistic regression equations to select those most likely to participate in

[27] Part of this screen requires computing potential Social Security benefits for eligible individuals not currently receiving OASDI benefits. SSI's status as "program of last resort" implies that individuals must apply for all other forms of support for which they are eligible, including Social Security, before receiving SSI.

SSI (generally, those who can expect relatively high benefits). We describe the computation of SSI benefit levels below.

The other cash and noncash transfers are all projected using regression-based strategies, rather than program rules. Most use a two-stage process, considering first whether income is present and then, if so, the projected value of the transfer (table 6). The equations use explanatory variables that correlate highly with eligibility criteria for these programs (e.g., assets, income, earnings changes, health status, presence of young children, poverty status, and so forth).

Living Arrangements and Income of Coresidents

Because moving in with relatives or friends is a commonly used strategy for avoiding poverty, and thus an important resource to take into account, MINT models living arrangements and the income of one's coresidents. The model uses separate algorithms for those ages 25 to 61 and 62 and older to model the decision to coreside (table 3). Predictors include the standard from the literature, including number of children, detailed marital history information, impending mortality and other demographics, and SSI receipt (to take into account SSI regulations on in-kind support and maintenance, or ISM).

MINT starts with observed SIPP coresidency status. After baseline, MINT imputes the characteristics of the persons with whom one coresides using a statistical match to historical SIPP family members of coresidents. In each age range, individuals/couples who are selected to coreside are classified into one of 16 recipient groups based on marital status, homeowner status, presence of children, and nativity. MINT selects an appropriate donor family among all families in the analogous donor group based on the wage-adjusted per capita income of the respondent.

Expenditures

The federal government's official poverty measure compares family money income to a series of thresholds that were originally computed in the 1960s as multiples of the cost of a nutritionally adequate diet. The thresholds vary by family size and whether the householder is under or over age 65. In recent years, the Census Bureau has developed a supplemental poverty measure (SPM) that takes into account certain kinds of noncash income and certain expenses in addition to food, including taxes and out-of-pocket expenses for medical care (Short 2012).

To help compute supplemental poverty, MINT7 simulates both premium and non-premium out-of-pocket medical expenditures. MINT7 first assigns health insurance coverage to one of eight types: employer-provided health insurance; privately purchased nongroup insurance; Medicare with employer coverage; Medicare with a gap policy; Medicare only; Medicaid only; Medicare Medicaid dual; and uninsured. Coverage depends on age, family income, and access to employer benefits (own or spouse). Premiums vary depending on the type of coverage.

For calculating out-of-pocket non-premium expenses, MINT7 uses a two-stage process. It first determines whether an individual or family has these expenses and then projects the amount given presence of expenses (table 7). Both stages use information on the individual's type of health insurance coverage. Implementing these equations required building a detailed representation of insurance status, including a representation of how the Affordable Care Act

(ACA) is expected to change coverage as it phases in. As with other functions, a wide array of demographic and economic predictors helps to explain these expenditures.

OASDI and SSI Benefit Calculators

OASDI: The MINT Social Security benefit calculator was developed by analysts in SSA's ORP. This calculator contains extremely detailed rules for computing benefits, taking into account one's own and one's spouse's lifetime earnings; timing of retirement, disability, and death; and other key benefit determinants.[28] It also includes many nuanced aspects of the benefit calculation, including the Government Pension Offset (GPO), RET, and Windfall Elimination Provision (WEP).

MINT7 projects current law scheduled Social Security benefits. The long-term projections do not reduce benefits when OASI or DI trust fund balances are depleted, although the strength of MINT is that it allows the user to examine the distribution of income under alternate Social Security policy.

SSI: MINT's SSI calculator similarly mimics rules and regulation from SSI law. It includes stylized state supplements, with parameters derived from TRIM, which in turn relies on SSA's publication *State Assistance Programs for SSI Recipients*. MINT uses baseline state information from the SIPP (or from the donor SIPP record in the case of post-baseline immigrants and the extended cohorts) in the assignment of state supplements. The model does not project state-to-state migration.

Income and Payroll Tax Calculators

MINT's income tax calculator is adapted from one Jon Bakija developed. To obtain quantities that MINT does not project, for example, capital gains and charitable deductions for itemizers, MINT statistically matches members of the sample to tax units on an Internal Revenue Service SOI public use file, which has information on key fields from the federal income tax form.

MINT7 uses current law federal tax parameters through December 2013. To compute tax liabilities into the future, MINT makes many assumptions about the personal income tax code. Users should be cognizant of the uncertainty in tax law over extended periods and thus the stylized nature of these assumptions.[29] But the ability to understand how net income will change offsets these limitations for some analyses. State tax parameters are more dated, last updated in 2004.

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[28] MINT tracks multiple spouses, enabling the calculator to compare benefits for those with multiple entitlements (e.g., because a previous marriage ended in divorce).

[29] MINT includes historic federal tax parameters through 2013 and state tax parameters through 2010, and prospective changes in tax law effective through 2023. We model future tax law differently for the short-term and long-term projections. For the short-term projections (through 2023), we hold current law tax rates constant and adjust the brackets for projected changes in the consumer price index. We hold the Social Security taxation thresholds at their current law values, because Congress chose intentionally not to index them for inflation when enacting these rules in 1983 and 1993 in order to increase over time the share of Social Security benefits subject to tax. For the long-term projections, we indexed exemptions and bracket widths of both the regular income tax and the alternative minimum tax to wages instead of prices.

Calculations of payroll taxes are straightforward given earnings, coverage, and the schedule of rates and the taxable maximum.[30] The calculated payroll tax on the final file includes only the worker's share calculated at family level, but users can compute alternatives that look at individuals and/or include both the employer and employee share.

Total Income Calculations, Including Poverty and Supplemental Poverty

Once all the MINT projections are complete, users can combine income and expenses to compute alternative measures of economic well-being, including how family incomes relate to the federal poverty level (FPL) and the SPM. Users can also evaluate how changes to Social Security and SSI benefits influence these measures or how further changes to economic structures and outcomes, like the pension landscape and the stock market, will affect them. With every model simulation, MINT automatically generates a large number of analytic tables that compute total incomes and poverty rates, both at points in time and at various ages (for example, 62 and 67). Many of the MINT products cited in table 1 present these projections.

Recommendations for Use, Including Policy Analyses

When using MINT for policy analysis, it is important to adhere to guidelines used with other survey data. For example, projections for smaller population or beneficiary groups are less reliable than those for larger ones, so users will want to take care about drawing inferences from a small number of unweighted cases. Similarly, users may want to examine percentiles rather than (or in addition to) means when examining quantities that are highly skewed in the United States and thus in MINT.[31] Earnings, wealth, asset income, and medical expenses are the most prominent examples. Given the enormous number of assumptions incorporated into MINT's long-range projections, users may wish to avoid the appearance of excessive precision when presenting certain estimates, especially when using nominal dollars. For example, analysts might consider rounding certain quantities in situations when one is not examining changes. Such situations would include characterizations of the future wealth distribution.

Because MINT projects all the way through, and even beyond, the 75-year projection horizon employed for the Trustees' Report, users may wish to avoid focusing on a single point in time when examining a proposal to change Social Security that has a time path that changes greatly over time (for example, benefit reductions are highly backloaded). Similarly, users may wish to avoid focusing exclusively on very distant projection years when this is not necessary. (for example, because a proposal phases in and effects stabilize relatively quickly), given that MINT's great strength is its observed data on real individuals. New retirees in 2070, for example, are just children today, and so their future in MINT is entirely simulated. With long-run projections, the issue of whether to present estimates in nominal, price-indexed, or wage-indexed terms also arises. One solution is to present multiple estimates, or when presenting just one, to

[30] The Trustees' file, used in many important MINT calculations, includes the historical and projected OASI, DI, and Hospital Insurance tax rates.
[31] Alternative or supplemental approaches include examining means excluding the top cases—for example, the top 5 percent of asset income holders—or calculating means by income percentile.

explain how using other measures does or does not change the story (see discussion in Butrica, Iams, and Smith 2003).

Another issue is how to compare alternative changes to the OASDI program that achieve different cost savings or rely on a different mix of costs savings between the payroll tax and benefit sides of the program.[32] Lifetime measures of benefits and taxes, and measures that relate these quantities to one another, can help display how changes affect both beneficiaries and taxpayers.

BEHAVIORAL RESPONSES

One sometimes controversial aspect of using a model like MINT is determining how to account for changes in behavior that might result from changes to policy parameters (say, the payroll tax rate or the early retirement age). Researchers differ in estimates and expectations of how large responses are likely to be. Historical data from which to estimate potential effects and analytic techniques may be insufficient: there are often few natural experiments for policy changes of significant magnitude under analogous economic and demographic circumstances for retirees and the disabled.

MINT has a limited capacity to account for policy changes that are captured in the estimated model parameters. For example, an increase in the full retirement age will have some modest effects on earnings and OASDI claiming.[33] Users uncomfortable with the default assumptions can impose an alternative response that is reasonable given expert judgment. In such circumstances, it is often helpful to test sensitivity of outcomes over a range of options (i.e., best guess, high, and low) derived from the best literature on the policy or process. Larger changes to Social Security, taxes, or other benefits are likely to lead to more sizable behavioral responses, and thus more likely to call for sensitivity analyses, than more modest changes.

USER TOOLS

Because many analysts use MINT, we have developed a number of tools that permit MINT users to easily compare outcomes across model runs, cohorts, time, and other characteristics. Similarly, MINT's highly parameterized source code facilitates developing and processing simulations with alternative assumptions about Social Security law or core processes (like mortality or wage growth).

[32] Favreault and Steuerle (2012), for example, compare alternative counterfactuals
[33] Typically, changes to Social Security benefits are modeled as a post-process without rerunning the model or changing any behaviors.

CONCLUSIONS

MINT is a large, complex model that has been under development for 15 years and is now used extensively by SSA analysts. We have tried to provide readers with a brief overview of the model. We recommend that users needing more detailed information consult the documentation identified in tables 1 and 3 through 6.

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Table 1. MINT History

Version	SIPP data used	Birth cohorts	Last year of admin data used	Trustees' assump-tions	Innovations/updates from prior version (beyond data and trustees' assumption updates)	Projection horizon	Technical documents	Selected related publications
MINT1	1990–93	Core: 1931–60	1996	N/A (see insert to report)	N/A	2020 focus, but extends to 2027[a]	Toder et al. (1999); Panis and Lillard (1999)	Butrica and Iams (1999, 2000); Butrica, Iams, and Sandell (1999)
MINT3	1990–93	Core: 1931–60	SER/ MBR:1999 SSR: 1997 Numident: 1998	2001; subsequent update to 2004	Added iterative (dynamically recursive), year-by-year processing, including retirement model (based on premium value); added work limitations, health status, living arrangements, and SSI.	2020 focus, but extends to 2027[a]	Toder et al. (2002)	Butrica, Iams, and Smith (2003, 2004, 2007); Butrica, Smith, and Toder (2002); Favreault and Wolf (2004)
MINT4	1996	Core: 1926–72; extended: 1973–2017	SER:2000 SSR:1998 Numident/ MBR:2002	2004	Added DER data and modified many functions to accommodate uncapped earnings; separate self-employment from wage and salary earnings.	2099	Smith et al. (2005)	N/A
MINT5	1990–93, 1996	Core: 1926–75; extended: 1976–2018	2004	2006; subsequent update to 2008	Added fertility history. Substantially revised many algorithms. Estimated poverty measure.	2099	Smith et al. (2007)	Butrica et al. (2009); Smith, Michelmore, and Toder (2008).
MINT6	2001, 2004	Core: 1926–75; extended: 1976–2070	2007 updated to 2009	2009; subsequent updates to 2010 and 2011	Added younger disabled workers further into simulation period; added transfer income (means-tested and non-means tested); replaced dated job change model for pensions with SIPP-based models; developed more sophisticated ways to treat extended cohorts (e.g., directly model pensions rather than assign from donor file); modeled immigrants more directly.	2099	Smith et al. (2010)	Butrica and Smith (2012a, 2012b, 2012c); Butrica, Smith, and Iams (2012)
MINT7	2004, 2008	Core: 1926–79; extended: 1980–2068	2010	2012	Added health insurance coverage and out-of-pocket medical expenditures; added non-cash transfers. Estimated supplemental poverty measure.	2099	Smith and Favreault (2013); The Urban Institute (2013a,b)	Butrica, Iams, and Smith (2013); Favreault and Haaga (2013); Favreault and Smith (2013)

Note: Additional policy simulations using MINT are described on page 3.

a. 2027 is year 1960 cohort turns 67.

Table 2. MINT7 Starting Sample

	2004 SIPP	2008 SIPP	Extended cohorts	Post-baseline immigrants	Total
Number of observations	45,214	37,568	210,712	34,295	327,789
Match rates (unweighted/weighted):					
Summary Earnings Records	0.866/0.848	0.933/0.913	N/A	N/A	N/A
Numident	0.871/0.853	0.938/0.919	N/A	N/A	N/A
Master Beneficiary Record	0.407/0.377	0.438/0.384	N/A	N/A	N/A
Supplemental Security Record	0.112/0.107	0.122/0.114	N/A	N/A	N/A
Topical module data:					
Marital, migration, fertility, and disability history	topical module 2	topical module 2	from donor	from donor	N/A
Medical expenses and health care utilization	topical modules 3 and 7	topical modules 4 and 7	from donor	from donor	N/A
Retirement and pension plan coverage	topical module 7	topical module 3	from donor	from donor	N/A
Assets and liabilities	topical modules 3 and 6	topical modules 4 and 7	from donor	from donor	N/A
Employer-provided health insurance, work history	topical module 5	topical module 6	from donor	from donor	N/A
Annual income and retirement accounts	topical module 7	topical module 5	from donor	from donor	N/A
Functional limitations/disabilities	topical module 5	topical module 6	from donor	from donor	N/A

Note: Each panel of the SIPP contains four rotation groups. The survey starts in a different month depending on rotation group. Correspondingly, topical modules are fielded in different months depending on rotation group.

Table 3. MINT Summary Specification Table: Demographics, Including Health and Work Limitations

Process	Data	Form and predictors	For more information
Birth	PSID/NLSY	Self-reported (observed) SIPP fertility through SIPP panel. Completed fertility using nine separate logistic equations by marital status, parity. Predictors: age splines, duration since last birth, education, employment status, log of earnings, race, ethnicity, own mother was a teen mom indicator, own mother's education. Adjust post-hoc for DI status.	Rendall (2005; 2003); Table 2-17, Smith et al. (2010)
Death (see also Table 4: death, earnings, and disability)	SIPP 2001 to 2004, matched to Numident calibrated to OACT	Administrative data through 2010. Splicing method before age 67. Continuous time hazard for ages > 67: age splines, education, disability status, marital status, race, birth year, calendar year, permanent income.	Table 2-5, Smith et al. (2010)
Living arrangements	SIPP, 2001, 2004, and 2008	Separate logistic regressions for initialization and continuation for ages < 62 and ≥ 62. Predictors: age, gender, education, race/ethnicity, number of children born, household income, marital status, SSI eligibility and participation, remarriage indicator, health, home ownership, nativity, mortality, interactions.	Re-estimated under MINT7: Tables A2.15 and A2.16, Smith and Favreault (2013)
Characteristics of coresidents	SIPP 2004–08 donors	Statistical match by group (defined on the basis of age, marital status, homeowner status, nativity, and childbearing history) from SIPP-based donor file based on respondent's per capita income.	Page 6-7, Smith et al. (2010)
Health status (fair or poor)	Ages 51–67: HRS 1992–2010; Ages 68+: SIPP/ SER/Numident 2008	Logistic, separate initialization and then by lagged status (excellent or fair-poor): age, sex, education, race, ethnicity, DI receipt, survival; At older ages, entry is separate by gender, and includes wealth/home ownership, nativity, marital status, and lagged earnings.	Re-estimated under MINT7: Tables A2.3, A2.4, A2.7, and A2.8, Smith and Favreault (2013)
Work limitations ages 51 to 67	HRS 1992–2010	Multinomial logit: age, sex, education, health, race/ethnicity, DI receipt, survival (in initialization).	Re-estimated under MINT7: Tables A2.5 and A2.6, Smith and Favreault (2013)
Marriage	SIPP, 2001, 2004, and 2008	SIPP marriage history. Continuous time hazard model, separate by gender and race (black, nonblack). Age splines, calendar time, duration unmarried, number of previous marriages, race/ ethnicity, education, immigrant status, widowed indicator, permanent income.	Re-estimated under MINT7: Table A2.1, Smith and Favreault (2013)
Spouse characteristics	PSID and SIPP	Probability tables derived from the PSID and SIPP. Characteristics include race, Hispanicity, spouse age difference by sex and marriage number.	Panis and Lillard (1999)
Spouse match (i.e., pointer to a specific person)	Assumption	Minimum distance matching function, variables in function include birth year, education, race, Hispanicity, disability start date, marriage begin and end dates, DI status, marriage termination type.	MINT7 update

Process	Data	Form and predictors	For more information
Divorce	SIPP, 2001, 2004, and 2008	SIPP marriage history. Continuous time hazard model, separate by gender and race (black, nonblack). Age splines, duration married, calendar time, number of previous marriages, race, nativity, Hispanicity, education.	Re-estimated under MINT7: Table A2.2, Smith and Favreault (2013)
Immigration	SIPP calibrated to OACT and Homeland Security	Cloning method to impute new immigrants based on recent immigrants in the SIPP data. Net age and sex target population from OACT 2012. Source region and legal status shares from US Department of Homeland Security (2012a, 2012b)	Smith et al. (2010), chapter 2, section VI
Emigration	SIPP	Restricted to immigrants (i.e., the native born do not emigrate). Hazard function based on age, source region, time in the US, individual-specific permanent error term.	Dowhan and Duleep (2002)
Institutionalization at ages 62 and older	SIPP, 1990–93	Logistic regression. Age, marital status, education, race, nativity, homeowner status, health status, indicator dies within next two years.	Toder et al. (2002), chapter 7 (Table 7-2)
Link POLISIM target file to MINT donors for extended cohorts (characteristics and earnings before age 32)	POLISIM 2012 and MINT7	Minimum distance function statistical match. Match variables include race, education, marital status, immigration age, foreign born status, immigrant source region (developed, undeveloped).	Smith et al. (2007), chapter 5

Note: SIPP matched data refers to SIPP matched to SER/DER/MBR Numident.

Table 4. MINT Summary Specification Table: Employment, Earnings, Disability Insurance

Process	Data	Form and predictors	For more information
DI receipt, earnings, and employment status for 1951–2010 for all ages	SIPP matched data	Observed from matched earnings records. For non-match cases, use hotdeck statistical match. Match variables include age, gender, death indicator, DI status, SSI status, report making a DC contribution on the SIPP, mean monthly earnings (7 categories), immigration age, immigrant source region, earnings status, education, race/ethnicity, class of worker.	Smith et al. (2010), chapter 4, section II
Years 2011+:			
Earnings, disability, and death through age 67 (later processes overwrite never-DI beneficiaries' post-age 54 earnings)	SIPP calibrated to OACT	"Splice" 5-year segments using statistical matching algorithm (hotdeck); variables in hotdeck match include age, gender, DI benefit indicator, number of years worked out of the last five, average earnings in last five years, work in year 5 of the match period, work in year 4 of match period, lifetime earnings quintile by cohort and sex, education, race/ethnicity, uncovered worker indicator, self-employed indicator, SSI receipt.	Smith et al. (2010), chapter 4 Toder et al. (2002), chapter 2
Earnings ages 55 through "retirement" for never-disabled	SIPP (2004 and 2008) matched to DER	"Trajectory method": standard age-earnings profile, separate by sex and education group, from fixed effects model. Predictors: age, cohort for women, 0.3 percent of high-earnings observations are capped (caps differ by education group). Capped earnings are reapplied after regression prediction is solved.	Re-estimated under MINT7: Tables A2.9 and A2.10, Smith and Favreault (2013)
"Retirement"	HRS matched data	Separate models by marital status: replacement rate from Social Security, pension accruals, permanent earnings, age, education, health/work limitations status, nativity, self-employment, spouse characteristics (age, permanent income, pension characteristics) for married people, financial assets.	Smith et al. (2007), tables 7-1 and 7-2
Earnings for retirees, ages 55 to 61	HRS matched data	Separate entry and exit models: age, education, gender, lifetime earnings, work limitations, ethnicity/race, wealth (housing and financial).	Re-estimated under MINT7: Table A2.11, Smith and Favreault (2013)
Employment and earnings for OASI beneficiaries ages 60 to 69	SIPP (2004 and 2008) matched to DER	Four logistic participation models (separate entry and exit models for claiming age and subsequent ages) and five separate ordinary least squares (OLS) models for earnings for similar groups. Age, education, gender, health status, marital status, recent earnings, lagged employment/employment duration, lifetime earnings, incentives in OASI (non-contributory, dual entitlement), pension indicators.	Partially re-estimated under MINT7: Table A2.13, Smith and Favreault (2013)
Employment and earnings at ages 70 and older	SIPP (2004 and 2008) matched to DER	Employment modeled using separate equations based on work status last period. Age, education, gender, health status, wealth, lagged employment, duration of employment, recent earnings, lifetime earnings.	Re-estimated under MINT7: Table A2.14, Smith and Favreault (2013)

Table 5. MINT Summary Specification Table: Pensions (Including Job Characteristics)

Process	Data	Form and predictors	For more information
Pension coverage for job changers	SIPP 2001–04	Logistic regression: age, gender, education, ethnicity, nativity, earnings, job sector, OASDI coverage share, union status.	Tables 5-4 and 5-5, Smith et al. (2010)
Job change	SIPP 2001–04	Age-centered logistic regression: age, gender, education, Hispanicity, nativity, number of children, job tenure and job tenure squared, job sector, earnings and earnings change, union status, OASDI coverage status.	Table 5-1, Smith et al. (2010)
Job sector	SIPP 2001–04	Multinomial logit: age, gender, education, race, lagged job sector, earnings and earnings change, union status, region (DC indicator), OASDI coverage status and share.	Table 5-2, Smith et al. (2010)
Union status	SIPP 2001–04	Logistic regression: lagged union status, gender, education, race/ethnicity, earnings, job sector, OASDI coverage share.	Table 5-3, Smith et al. (2010)
Risk tolerance	SCF 1998–2007	Multinomial logit: age, education, marital status.	Table 5-8, Smith et al. (2010)
Contributions to DC pensions	1996 SIPP/DER match	Logit for whether contributes conditional on offer, tobit for amount contributed. Predictors: age, age squared, gender, marital status, number of dependents, jointly offered or frozen plan, contribute two years ago, own earnings/average wage, job tenure (1, 2, 3–4), spouse earnings/average wage. Participate for prior year contributors: self-employment status, autoenrollment dummy*tenure=1. Amount given participation: race, employer contribution match, job tenure (≤ 1 year, 5+ years), homeownership status, jointly offer or frozen plan.	Tables 8-3 and 8-4, Smith et al. (2007)
Election of single life pension	HRS 1992–2000	Probit by gender: pension wealth, non-pension wealth, marriage duration, health status, marriage duration, race/ethnicity, education.	Table 8-11, Smith et al. (2007)
Decision to save lump sum distribution	SCF	Look-up table by age (8 groups) and size of distribution (4 groups). Probability of taking a lump sum distribution decreases with age and higher account balances.	Adapted from Moore and Muller (2002)

Table 6. MINT Summary Specification Table: Wealth

Process	Data	Form and predictors	For more information
Home purchase (among renters)	PSID 1968–94	Annual logistic regression hazard. Predictors: present value of lifetime earnings/cohort average (husband + wife), present value of lifetime earnings/cohort average squared (husband + wife), number of years with earnings above the taxable maximum (husband + wife), current year earnings/average wage (capped at 2.46) for husband and wife, single dummy, married dummy, black dummy, number of children under age 18, first child born indicator, self-employed dummy, number of years divorced.	Toder et al. (2002), chapter 6
Home sale (among homeowners)	PSID 1968–94	Annual logistic regression hazard. Predictors: present value of lifetime earnings divided by the cohort average (husband + wife), present value of lifetime earnings/cohort average squared (husband + wife), husband current year earnings/average wage (capped at 2.46), wife current year earnings/average wage (capped at 2.46), age*Hispanic, age*self-employed, age splines, married dummy, widowed dummy, single female dummy, divorced duration, first child born dummy, number of children less than 18.	Toder et al. (2002), chapter 6
Housing wealth ages 25 to 49, dependent variable= ln(home equity/average wage)	PSID 1968–94	Separate random effects models for unmarried and married homeowners. Individual-specific permanent error term imputed from PSID. Predictors: own present value of earnings/cohort specific average, former spouse present value of earnings/cohort specific average, average capped earnings in last five years, number of years of earnings above taxable maximum, age splines, age interactions (black, Hispanic, college, never married).	Toder et al. (2002), chapter 6
Housing wealth ages 50 to retirement, dependent variable =ln(home equity/ average wage); implemented as a change in assets from the prior year	HRS 1992–2004; calibrated to SCF	Separate random effects models for single and married homeowners. Predictors: age, age interactions (health, pension, self-employment, education, number of children ever born, race, male headed family indicator), number of years of earnings above the taxable maximum, present value of lifetime earnings/cohort average, spouse education.	Smith et al. (2007), chapter 3

Process	Data	Form and predictors	For more information
Nonhousing wealth to age 49, dependent variable=ln(home equity/average wage + 0.2)	PSID 1984–94; initial SIPP data calibrated to SCF	Separate random effects models for single and married. Individual-specific permanent error term imputed from PSID. Predictors: present value of per capita shared earnings/cohort specific average, mean earnings/ average wage in past five years capped at 2.46*average wage, age splines, cohort dummies, number of years of earnings above taxable maximum, age interactions (education, race, homeowner, marital status; for married, wife self-employed, wife education, husband race, husband education, husband self-employment), widowed and divorce intercepts.	Toder et al. (2002), chapter 6
Nonhousing wealth age 50 to retirement, dependent variable= ln(financial assets/average wage + 0.02); implemented as a change in assets from the prior year	HRS; initial SIPP data calibrated to SCF	Separate random effects models for single and married. Predictors: age and age interactions (homeowner and renter dummies, number of children ever born, health, DI beneficiary, race, ethnicity, male dummy, DB and DC pension indicators, self-employment, widowed dummy, number of years ever married, own and spouse education, own and spouse self-employed), present value of earnings/cohort average, number of years of earnings over taxable maximum.	Smith et al. (2007), chapter 3
Non-housing wealth from retirement to death, dependent variable=ln(financial + retirement account assets/average wage + .02); implemented as a change in assets from the prior year	1984–93 SIPP data linked to SER	Separate OLS models for single and married. Predictors: homeowner, race, pension income receipt, average earnings/average wage age 50–60 > 1.2, widowed dummy, die within two years, husband or wife dies within two years.	Toder et al. (1999), chapter 7

Note: All functions use initial values from SIPP self-reports where available.

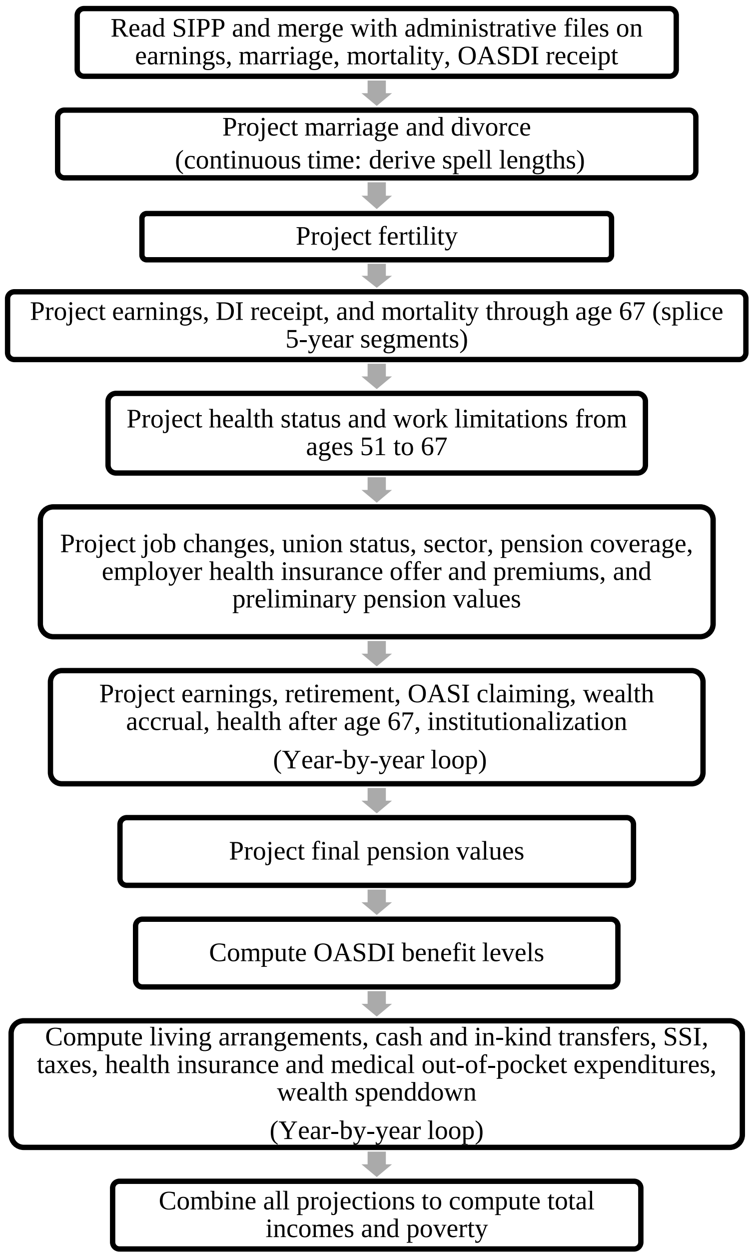
Table 7. MINT Summary Specification Table: Other Income Sources and Health Coverage and Expenditures

Process	Data	Form and predictors	For more information
OASI claiming	SIPP	Three separate hazard models for spouse only, low earners and high earners (defined based on relationship of lagged earnings to the exempt amount). Predictors: age, retirement indicator, spouse's claiming, pension coverage indicators, health status, marital status, wealth, lagged earnings, high earnings, lifetime earnings (PIA and present value of lifetime earnings).	2 equations re-estimated under MINT7: Table A2.12, Smith and Favreault (2013); spouses table 4-4 in Smith et al. (2010)
SSI participation among eligible individuals	SIPP	Separate models for new entrants and continuing beneficiaries in 3 age ranges: 25–61, 62–64, and 65 plus. Predictors: age, sex, education, nativity, marital status, expected federal benefit, Southern indicator, income, work limits, home ownership, years since last earned, total earnings years, lagged status, interactions with lag status. Uses TRIM state supplement data.	Young ages: Table 6-3, Smith et al. (2010); Older ages: unpublished tables
Means-tested transfers (TANF, general assistance)	SIPP (2001 and 2004 matched to DER and Numident)	Separate models for presence (logistic) and amount (OLS). Predictors: age, sex, education, marital status, number of children, homeowner status, survival, type and composition of income, state dummies, earnings and earnings changes.	Table 6-5, Smith et al. (2010)
Non-means-tested transfers (workers' comp, UI, temporary disability)	SIPP (2001 and 2004 matched to DER and Numident)	Separate models for presence (logistic) and amount (OLS). Predictors: age, sex, education, marital status, number of children, homeowner status, survival, type and composition of income, dummy for states with TDI, earnings and earnings changes, lagged SSI, health status, wealth.	Table 6-6, Smith et al. (2010); Presence re-estimated under MINT7: Table A2.17, Smith and Favreault (2013)
Noncash transfers (housing assistance, Low Income Home Energy Assistance Program, WIC, SNAP)	SIPP 2001–08	Separate models for presence (logistic, both initial and subsequent), amount (OLS). Predictors: age, age squared, education, race, Hispanicity, nativity, marital status, health status, homeowner status, financial assets/average wage, year dummies, earnings and earnings changes, recent employment, family income/poverty (5 groups), dummy for states with TDI, other state dummies, metro status, SSI and OASDI, means-tested benefits, number and ages of children. When projecting subsequent receipt: lagged receipt status and lagged household benefit amount/average wage.	New in MINT7: Tables A1.7 and A1.8, Smith and Favreault (2013)
Health insurance coverage offered by employer	2004, 2008 SIPP	Employer health insurance offer: logistic regression among workers. Predictors: firm size (8 groups), region (4 groups), employer sector (4 groups), education, union, average earnings/average wage in last 3 years * sex, year ≥ 2014.	New in MINT7: Table A1.1, Smith and Favreault (2013)
Medigap purchase among Medicare beneficiaries	MEPS 2007–11	Logistic: age, race, ethnicity, ln of household income/average earnings	New in MINT7: Table A1.2, Smith and Favreault (2013)
Out-of-pocket medical expenses	MEPS 2007–11	Logistic for presence, OLS for ln amount, separate by married/unmarried. Age, education, ethnicity/ race, detailed marital status, number of children, homeownership, wealth,	New in MINT7: Tables A1.3 through A1.6,

Process	Data	Form and predictors	For more information
		detailed health insurance status indicators, SSI and OASDI, earnings and earnings changes, metropolitan status indicator, institutionalization indicator, state indicators.	Smith and Favreault (2013)

Note: All functions use initial values from SIPP self-reports or administrative records for starting values where available.

Figure 1. Stylized Representation of the MINT Processing Sequence



Note: **This process is stylized. For a more complete representation with references to key file, see The Urban Institute (2013b), pages 8 and 9.**

Figure 2. MINT7 Splicing of Earnings, Mortality, and Disability

DONOR FILE

	Age 50	Age 51	Age 52	Age 53	Age 54
Donor 1	$15,000, no DI, alive,	$16,000, no DI, alive	$16,000, no DI, alive	$17,000, no DI, alive	$18,000, no DI, alive
Donor 2	$50,000, no DI, alive	$52,000, no DI, alive	$54,000, no DI, alive	$55,000, no DI, alive	$54,000, no DI, alive
Donor 3	$30,000, no DI, alive	$31,000, no DI, alive	$6,000, enter DI, alive	$0, receive DI, alive	$0, receive DI, die

Recipient 1 matches to donor 1

Receipient 2 matches to donor 2

Recipient 3 matches to donor 3

RECIPIENT FILE

	Age 45	Age 46	Age 47	Age 48	Age 49
Recipient 1	$14,000, no DI, alive	$15,000, no DI, alive	$14,000, no DI, alive	$15,000, no DI, alive	$15,000, no DI, alive
Recipient 2	$49,000, no DI, alive	$48,000, no DI, alive	$49,000, no DI, alive	$50,000, no DI, alive	$51,000, no DI, alive
Recipient 3	$28,000, no DI, alive	$29,000, no DI, alive	$31,000, no DI, alive	$30,000, no DI, alive	$32,000, no DI, alive

RESULTING "SPLICED" FILE

	Age 45	Age 46	Age 47	Age 48	Age 49	Age 50	Age 51	Age 52	Age 53	Age 54
Recipient 1	$14,000, no DI, alive	$15,000, no DI, alive	$14,000, no DI, alive	$15,000, no DI, alive	$15,000, no DI, alive	$15,000, no DI, alive	$16,000, no DI, alive	$16,000, no DI, alive	$17,000, no DI, alive	$18,000, no DI, alive
Recipient 2	$49,000, no DI, alive	$48,000, no DI, alive	$49,000, no DI, alive	$50,000, no DI, alive	$51,000, no DI, alive	$50,000, no DI, alive	$52,000, no DI, alive	$54,000, no DI, alive	$55,000, no DI, alive	$54,000, no DI, alive
Recipient 3	$28,000, no DI, alive	$29,000, no DI, alive	$31,000, no DI, alive	$30,000, no DI, alive	$32,000, no DI, alive	$30,000, no DI, alive	$31,000, no DI, alive	$6,000, enter DI, alive	$0, receive DI, alive	$0, receive DI, die