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Validating Longitudinal Earnings in Dynamic Microsimulation Models: The Role of Outliers

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The Program on Retirement Policy

A crosscutting team of Urban Institute experts on Social Security, labor markets, savings behavior, tax and budget policy, and microsimulation modeling ponder the aging of American society.

The aging of America raises many questions about what's in store for future and current retirees and whether society can sustain current systems that support the retired population. Who will prosper? Who won't? Many good things are happening too, like longer life and better health. Although much of the baby boom generation will be better off than those retiring today, many face uncertain prospects. Especially vulnerable are divorced women, single mothers, never–married men, high school dropouts, and lower–income African Americans and Hispanics. Even Social Security—which tends to equalize the distribution of retirement income by paying low–income people more then they put in and wealthier contributors less—may not make them financially secure.

Uncertainty about whether workers today are saving enough for retirement further complicates the outlook. New trends in employment, employer–sponsored pensions, and health insurance influence retirement decisions and financial security at older ages. And, the sheer number of reform proposals, such as personal retirement accounts to augment traditional Social Security or changes in the Medicare eligibility age, makes solid analyses imperative.

Urban Institute researchers assess how current retirement policies, demographic trends, and private sector practices influence older Americans' security and decisionmaking. Numerous studies and reports provide objective, nonpartisan guidance for policymakers.

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Abstract

Rapid growth in the earnings of the highest earners over the past 25 years has contributed to strains on Social Security's finances and made projecting lifetime earnings on a year-by-year basis—already a complicated technical problem—even more challenging. This project uses descriptive techniques and high-quality administrative data matched to household surveys to explore questions about the changing earnings distribution. We describe high earners' characteristics, both at a point in time and over longer periods (from 1983 through 2010). We then evaluate how well SSA's MINT7 model projects inequality in the earnings distribution and the long-term characteristics of earnings paths.

Executive Summary

The distribution of Social Security payroll taxes and benefits has changed dramatically over the past three decades, largely because of increasing dispersion in earnings. Earnings have increased particularly rapidly for the very highest earners (e.g., Bakija, Cole, and Heim 2010; Kopczuk, Saez, and Song 2007, 2010; Piketty and Saez 2003, 2010). This dispersion affects financing and distributions for the Old-Age, Survivors, and Disability Insurance program through the contribution and benefit base (the taxable maximum), the progressive benefit formula, and the average wage index, which determines overall benefit levels (for discussion, see for example, Favreault 2009). Some research hypothesizes that dispersion also increases benefit take-up for Social Security's Disability Insurance component by raising benefit replacement rates for the lowest lifetime earners (Autor and Duggan 2006), though the size of the effect is the subject of debate (Muller 2008).

This paper characterizes high earnings and then high-earnings spells, identifying the degree to which they are transitory or tend to persist throughout a career. Our analyses rely on data from the Survey of Income and Program Participation matched to Social Security Administration and other government records on earnings, benefit receipt, mortality, and nativity. We examine both earnings over the taxable maximum ($113,700 in 2013) and earnings of at least 4.5 times the average wage, equal to just over $200,000 in 2013. We also look more broadly at earnings dynamics over the life course, considering, for example, transitions across quintiles and total work years over various thresholds.

We first document how high earnings prevalence varies by age, gender, nativity and country of origin, race/ethnicity, parity, and geography (metropolitan status and state, classified by earnings quintile). We also look closely at individuals' skill levels, work histories, and characteristics of their current jobs. Not surprisingly, we find wide differentials across these groups, both at a point in time and over extended periods. Almost all these differentials persist after controlling for the other characteristics, and evidence suggests that certain differentials, especially those related to skill, industry, and geography, may be growing over time. We also find that although a significant share of earners exceed these thresholds just once or twice in a career, many individuals earning enough to exceed these levels tend to remain over them for much of their careers. Earnings transitions in the labor market more broadly, as measured by quintile transitions, retain a similar stickiness.

We then consider implications of these patterns for proposals that would raise Social Security's contribution and benefit base. We find that median changes in Social Security replacement rates tend to be quite modest in a simple hypothetical scenario in which the taxable maximum is lifted retrospectively. For a minority, however, reductions could be large, especially if Social Security did not pay additional benefits on the additional contributions.

Projection models that use regression equations and splicing techniques to capture this underlying continuity in high earnings tend to produce reasonable results along these longitudinal dimensions. We suggest areas for future testing and sensitivity analysis.

ACRONYMS

AIME	Average Indexed Month Earnings
AR-1	Autoregressive (First-order)
AWI	Average Wage Index
DER	Detailed Earnings Record
DI	Disability Insurance
CBO	Congressional Budget Office
CBOLT	Congressional Budget Office Long-Term dynamic microsimulation
CQ	Covered quarter (for OASDI)
DC	Defined Contribution
DI	Disability Insurance
DYNASIM	Dynamic Simulation of Income Model
FT/PT	Full-time/Part-time
GDP	Gross Domestic Product
GED	General Equivalency Diploma
HI	Hospital Insurance (Medicare)
HRS	Health and Retirement Study
LDC	Less- [Economically] Developed Country (based on per capita GDP in 2010)
MBR	Master Beneficiary Record
MDC	More- [Economically] Developed Country (based on per capita GDP in 2010)
MINT	Modeling Income in the Near Term
NBER	National Bureau of Economic Research
OASDI	Old-Age, Survivors, and Disability Insurance
OASI	Old-Age and Survivors Insurance
PIA	Primary Insurance Amount
SER	Summary Earnings Record
SIPP	Survey of Income and Program Participation
SSA	Social Security Administration
SSI	Supplemental Security Income Program

Introduction

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This paper characterizes high earnings and high-earnings spells, identifying the degree to which they are transitory or tend to persist throughout a career. Our analyses rely on data from the Survey of Income and Program Participation (SIPP) matched to Social Security Administration (SSA) and other government records on earnings, benefit receipt, mortality, and nativity. We examine both earnings over the taxable maximum and over higher earnings levels.[2] We also look more broadly at earnings dynamics over the life course, considering, for example, transitions across quintiles.

We find that individuals whose earnings are high enough that they exceed the Social Security earnings cap tend to remain above the cap for much of their careers. In the economy more broadly, earnings transitions retain a similar stickiness. Projection models that use regression equations and splicing techniques to capture this continuity tend to produce reasonable results along these longitudinal dimensions, but there is room for improvement. We suggest areas for future testing and sensitivity analysis.

We organize our paper as follows: we begin by describing how OASDI treats high earnings. We then discuss past literature on growth in earnings dispersion. We address two separate strands of the literature: those studies that attempt to explain trends and those that provide guidance on generating forecasts of lifetime earnings. We then discuss our data and methods, and follow with our results. We begin with descriptive data on historical patterns for high and low earnings over the life course and their implications for Social Security benefits. We then turn to comparisons of the forecasts from one prominent model, SSA's Modeling Income in the Near Term (MINT), to the historical patterns.[3] We conclude with some summary comments and suggestions for future research.

Background on Social Security's Payroll Tax Contribution Base

Under current law, workers pay Social Security payroll tax only on their first $113,700 in OASDI-covered earnings in 2013.[4] This value grows annually as average wages rise. Similarly, workers only accrue benefits through this earnings level. Social Security thus refers to this amount as the contribution and benefit base, but it is known more colloquially as the taxable maximum (sometimes inverted to "maximum taxable earnings" or shortened to "taxmax").[5] The *Social Security Handbook* (section 1300) details the types of compensation subject to OASDI payroll taxation. These include not just wages and salaries in the form of cash, but also the cash value for compensation paid in another form, like bonuses, commissions, fees, vacation pay, cash tips of $20 or more per month, and severance pay. They also can include profit-sharing and stock bonus plans under certain conditions. Social Security exempts from taxation in-kind meals, lodging, and gym facilities, but not cash payments in place of these amenities. Workers currently do not need to pay payroll tax on certain income deferrals, like contributions to medical and dependent care spending accounts[6] or the value of employer-sponsored health insurance.

Over the past several decades the share of total earnings below the cap has declined markedly, from around 90 percent in 1983 to around 84 percent in 2010 (figure 1). At the same time, the share of working individuals earning over the cap has remained roughly constant at about 6 percent, with the share of women over the cap increasing at the same time that the share of men has declined (figure 2). These two trends (declining share of covered earnings yet a constant share of workers earning over the taxable maximum) occur simultaneously because the amount earned by those over the cap has increased. Figure 3, derived from data from Kopczuk et al. (2007), shows that the earnings share of the top 5 percent of the earnings distribution grew by about 5.5 percentage points from 1983 to 2004, with roughly 4 percentage points of the growth coming from the top half of one percent of earners. Social Security actuaries estimate that for the share of earnings taxed by the program to reach 90 percent, the taxable maximum would increase to about $239,400 in 2013 from its current level of $113,700 (SSA 2012c).

Previous Research on Longitudinal Earnings and High Earnings

High earnings and earnings dispersion: estimates and causes

While the literature on earnings inequality has proliferated in recent years, studies that focus specifically on this declining taxable share, rather than more broadly on upper percentiles of the earnings distribution, are relatively rare. In its 2007 report, the Social Security Advisory Board's Technical Panel on Assumptions and Methods described a pressing need for better research on trends in the taxable share and how they affect Social Security financing (Technical Panel on Assumptions and Methods 2007). The 2011 Technical Panel similarly suggests that this remains a central unresolved issue for projecting OASDI costs (Technical Panel on Assumptions and Methods 2011).

The literature on increased earnings dispersion, and thus implicitly the declining taxable share, suggests a wide array of explanations for the recent trends. Consistent with figure 3, rapid growth in the earnings of extreme outliers seems to be a highly promising explanation (e.g., Atkinson, Piketty, and Saez 2011; Bebchuk and Grinstein 2005; Frydman and Jenter 2010; Frydman and Saks 2010; Gordon and Dew-Becker 2007; Piketty and Saez 2003, 2010). However, what has caused this high earnings explosion is less clear. While some point to changing labor force composition (education, gender, nativity, and age), these effects appear to be relatively modest (e.g., Cheng 2011; Favreault 2011). Analysts point to the especially high returns that the truly exceptional can garner (e.g., Rosen 1981), growing importance of fringe benefits in employee compensation (e.g., Pierce 2010, Burtless and Milusheva 2013), skill-biased technological change (e.g., Autor, Katz, and Kearney 2006, Autor and Dorn 2013), changing institutions—particularly the decline of unions and worker bargaining power (e.g., DiNardo, Fortin, and Lemieux 1996; Levy and Temin 2007)—geographic concentration of higher wage workers (e.g., Gordon 2009; Moretti 2013), responses to government tax policies, more globalized labor markets (which can lead to downward pressure on wages, especially at certain points in the wage distribution [Autor, Dorn, and Hanson 2013]), and cyclical effects.

Longitudinal earnings

Favreault and Steuerle (2008) describe how lifetime earnings have varied across cohorts and educational groups, separately for men and women. One of the more striking features of the distribution is the rapid change in women's histories. Their estimates suggest that women's work histories, particularly total years worked, should continue to increase through about the 1959 birth cohort, with women's work histories stabilizing for subsequent cohorts in terms of number of years worked (work intensity and earnings still increase, but change in work years is more limited). They also find that by late career, less-educated workers have worked fewer years than more educated workers, and that this gap may be growing, perhaps due to increased selectivity of less-educated workers. These career-length differentials are greater for women than men, and there is a good deal of heterogeneity within groups. Nonetheless, this pattern persists even after one accounts for immigration status and experience with the DI program.

Leonesio and Del Bene (2011) compare earnings dispersion at points in time with long-run (twelve-year) dispersion in earnings using a wide variety of measures using high quality administrative data. They find that from 1981 through 2005, men's earnings grew increasingly dispersed. Women's earnings dispersion grew less than men's earnings dispersion, with estimates of the magnitude of growth for women ranging widely and depending importantly on how researchers treat women with intermittent work histories in their calculations.

Kopczuk et al. (2007, 2010) examine transitions among various percentiles in the earnings distribution, also using Social Security earnings data. They consider such transitions as movements between quintiles over eleven-year periods (from early to mid-career, from mid- to late career, and from early career to late career) and how mobility varies over ten-, fifteen-, and twenty-year periods. They document that mobility is greater the longer the intervals one considers, but that there is comparatively less mobility into the top 1 percent. They examine issues such as where individuals in the top 1 percent were earlier in their careers. They find that the vast majority were in the top 5 percent of the distribution 10 years earlier. In recent years, only about 10 percent of the top 1 percent occupied a position in the bottom 80 percent of the distribution 10 years earlier (so 90 percent were in the top 20 percent 10 years earlier).

As part of their validation analysis for a forecasting model, researchers from the Congressional Budget Office (2006) describe how lifetime earnings deciles compare to annual earnings deciles. Consistent with prior research, they find significant persistence in earnings (i.e., there is clustering on the diagonals of the transition matrices) and qualitative similarities between men's and women's transition matrices.

Previous Research on Modeling Lifetime Earnings at the Micro-Level

Dynamic microsimulation models generally rely predominantly on two separate strategies to forecast earnings, including those of the highest earners. The most common approach is to use a series of regression equations. These regression models typically use very complex error structures, with permanent and transitory components and close attention to heterogeneity in these components (for example, Congressional Budget Office 2006; Moffitt and Gottschalk 2008; O'Donoghue, Leach, and Hynes 2009; Schwabish and Topoleski 2012). An alternative to regression is statistical matching or splicing together segments of observed earnings histories, sometimes including other characteristics (Burtless, Sahm, and Berk 2002). Each approach has advantages and limitations. For example, some developers prefer to use regression methods as they allow more explicit control of key assumptions in the projection period. They also tend to have more detail and decision points (for example, hours of work, full-time/part-time) which the developer can alter in future simulations. Matching methods, in contrast, more directly ensure simultaneity and correlations among outcomes across the life history. Both approaches depend on the quality of the underlying data and the developer's selection of explanatory variables.

Splicing and regression methods handle outlier earnings in different ways. A splicing method replicates (i.e., resamples or "clones") individuals from the high and low tails in the proportions that they exist in the original sample (i.e., the “donors”) to the extent that individuals with similar characteristics populate the pool of individuals who will receive an earnings segment in the projection period (i.e., the “recipients”). Developers using regression models, by contrast, need to make explicit decisions about whether and how to include high (or very low) earners. Common approaches include modeling wages or earnings after transforming them into their natural logarithm and employing complex error structures to at least partially address outliers’ effects. But even beyond these two tactics, developers sometimes use other measures to explicitly address the extreme upper end of the distribution. If one includes extreme outliers in certain types of regression models, such cases can distort the estimate of the variance, generating excess variability in projected outcomes. Beyond these specification issues, measurement can be another problem. Topcoding may remove outliers in many estimation samples. Even when one has the benefit of administrative data, one cannot be entirely sure that very high (and similarly very low) earnings values do not reflect measurement error,[7] and one wants to use care not to correct measurement error asymmetrically (e.g., for high values but not low ones or the reverse).

Appendix 1 presents summary information on the specification of earnings projections in three prominent dynamic microsimulation models in the U.S.[8] Table A1.1 identifies some key features of each model’s approach to modeling lifetime earnings—for example, whether it primarily relies on regression or matching techniques. Table A1.2 describes in greater detail the earnings projection in MINT, the model that we evaluate in these analyses.

Data and Methods

This study uses data from five panels of the SIPP—1984, 1996, 2001, 2004, and 2008—matched to administrative earnings records, including the Summary Earnings Record (SER) and Detailed Earnings Record (DER), Numident data on mortality, nativity, and legal status, and

Master Beneficiary Record (MBR) data on program participation, to trace how various factors have contributed to payroll tax and benefit dispersion over the past three decades (through 2010). Most of our analyses focus on the 2004 and 2008 panels, as we are most interested in understanding the most recent patterns in high (and very low) earnings prevalence.[9] However, in order to describe changes over time and ensure reliable sample sizes in certain analyses, we make additional comparisons to data from the earlier SIPP panels. In a few cases where having the most recent possible data is paramount (for example, because of cohort effects among women) and we mainly care about fixed variables like birth cohort and gender, we use administrative data from as far as 2010 and screen for survival. Any sample choice has strengths and weaknesses. For example, the fact that much of 2009 was a recessionary year, with important effects on earnings and employment, complicates the focus on calendar years 2004 and 2009.

SIPP is a nationally representative survey of the noninstitutional population, with oversamples of individuals in lower-income households likely to participate in transfer programs (Westat 2001). The Census Bureau follows individuals in SIPP and re-interviews them every four months for a period of about three to four years, depending on the panel.[10]

Our data have a number of important limitations, posing challenges for our research, so we point out a few caveats. First, uncapped earnings (i.e., including earnings above the taxable maximum) are only available from the early 1980s, and the earnings cap was quite low in the 1950s through the mid-1970s.[11] Second, even administrative records contain reporting errors, and these may disproportionately affect high earners (see, for example, the discussion in Leonesio and Del Bene 2011). Third, when combining the household survey data with the administrative data, many cases do not match to the administrative records, and non-match rates differ by many important characteristics, including nativity and work history (see, for example, appendix table 2 in Favreault and Nichols 2011). Undocumented workers pose particular challenges. Fourth, the survey may underrepresent the very highest earners.[12]

To compensate for this third point, lack of representativeness of the cases matched to administrative records, we re-weight the sample in most descriptive analyses. Specifically, we increase the SIPP person weights in proportion to the probability that an individual would be an unmatched case.[13] In most tables, we also exclude immigrants whose legal status we impute to be “other-than-legal”, on the rationale that this group is not of primary interest for Social Security policy surrounding the taxable maximum and their earnings reports are not reliable. Researchers estimate that these individuals are about 3.5 percent of the U.S. population (authors’ calculations from Passel and Cohn 2011). We estimate that they are a disproportionate share, likely between a fifth and a quarter, of the non-matched cases and we likewise exclude them when computing the weight adjustment.

To compensate for likely missing data on the highest of high earners, we minimize use of aggregate statistics that are very sensitive to extreme cases (like the share of total earnings over the cap for certain types of workers) and focus instead on high earnings’ distributional incidence.

<u>Longitudinal description of high-earners’ experiences.</u> To characterize the trajectories of the highest earners, we focus on individual-level patterns. We consider several continuous metrics, like the total number and share of years above certain thresholds and transition probabilities given the length of one’s current spells.[14] We also construct earnings transition matrices, following Leonesio and Del Bene (2011) and Kopczuk et al. (2007).

<u>Validation of MINT7 earnings skewness.</u> For the portion of the project where we evaluate earnings trajectories in MINT, we focus on outliers, as they present challenges for

microsimulation model developers forecasting earnings, to determine whether MINT techniques have been adequate. Using tabulations from matched SIPP earnings data, we evaluate whether projected longitudinal patterns among relatively high earners are consistent with past patterns and evolve in a reasonable, consistent manner.

Historical Results

Who earns over the taxable maximum annually and over longer periods? How much do they earn?

We begin our discussion of the SIPP estimates by discussing the characteristics associated with earning above the taxable maximum. Table 1 first provides a simple description of the age/gender pattern in prevalence of earnings over the cap in 2004 and 2009. This table uses two separate definitions of who qualifies as an earner: any reported earnings and earnings of at least one covered quarter, set at $1,160 in 2013.[15] This latter threshold reflects the minimum earnings required to accrue entitlement toward Social Security benefits. The share with earnings above the cap increases through about age 40. Between the ages of 40 and 59, the share who earn over the cap is relatively flat. Around age 60, the share then begins to fall. At all ages, men are far more likely than women to earn above the cap, consistent with the historical data in figure 2. The age/sex pattern is consistent using both measures, but the level is about a percentage point higher with the lower bound of one quarter, reflecting both the significance of low earners to any measurement of labor force rates and the difficulty of measuring earnings through self reports.

Given that so few old and young workers earn over the taxable maximum, we restrict our sample in our next analyses to individuals ages 30 to 67. Here we consider earnings over the cap at a point in time, separately for men and women. We also examine earnings over the past 20 years, in this case restricting age further to just those ages 45 through 67.[16] This restriction may work better for describing patterns for men than for women, who are experiencing rapid cohort shifts in earnings. Our objective is to provide a broad overview of who in the labor force today earns over the taxable maximum or has experience over the cap. (Our subsequent longitudinal and regression analyses address some of the confounding factors, like age.)

Table 2 reveals that characteristics of individuals earning over the taxable maximum differ from those of their counterparts earning below the cap. For example, earning over the cap is, not surprisingly, associated closely with educational attainment. Among men, about half (53 percent) of those with a professional degree earn above the cap at a point in time, while over 70 percent earned over the taxable maximum at least once in the past 20 years. In comparison, only about one half of a percent of women with a high school degree or less earn over the maximum at a point in time, and less than two percent exceeded it cap over a twenty-year period.

Differences by race and ethnicity are statistically significant. Those who report their race as Asian or Pacific Islander are most likely to earn over the taxable maximum, with self-reported whites next most likely. Those who are African-American or Native American are far less likely to earn over the cap, usually a third to half less likely than whites, with a larger gap among men than among women. Hispanics of any race are least likely to earn above the cap, though the Latino population is younger than the population at large, so that partially explains the difference. (We address this type of confounding later in some multivariate analyses.)

Patterns in high earnings by nativity vary by the level of economic development of one's country of origin (table 3). Those who are foreign-born from countries with higher levels of economic development, defined by per capita Gross Domestic Product (GDP)[17], are the most likely to earn over the cap, followed by native-born adults and then immigrants from countries with lower levels of economic development. Married men are far more likely to exceed the taxable maximum than their non-married counterparts, but marital status is less closely associated with high earnings for women. Men who have had more children are more likely to exceed the cap, but women with more children are less likely.

One's current place of residence also appears to be an important correlate of having relatively high wages. Metropolitan status is closely associated with high earning for both men and women, as is being from a higher-wage state.[18] These patterns hold at a point in time and over the twenty-year period, during which some in our sample may have moved. Because the SIPP is not designed to provide representative estimates on a state-by-state basis, Table A2.1 displays further data on the share of earnings OASDI taxes by state from SSA records (SSA 2012b).These estimates cannot give a definitive picture, as they mix two separate issues: coverage of earnings, especially state and local employee earnings, but also federal and railroad earnings, and earnings over the taxable maximum. [19] Nonetheless, the estimates suggest patterns in the geographic distribution of aggregate earnings over the taxable maximum.[20] Woo et al. (2011, 2012) use self-reported data to describe prevalence of earnings above the taxable maximum by state.

Table 4 provides this same information by current job characteristics, including occupation, industry, and firm size. Individuals who earn over the cap are concentrated in certain occupations (managerial, professional, sales). [21] Those with missing data are often partial year workers who earn above the maximum at low rates. They are also disproportionately represented in some industries (professional, financial, information). At a point in time, they are more likely to be working at larger firms, but current firm size generally appears less closely related to history of earning over the thresholds than do factors like occupation and industry, which may reflect more permanent attributes.

Table 5 examines work experience, including current work hours, tenure on the current job, and OASDI covered work history (i.e., years of covered earnings from 1951 to present).[22] The rationale for looking at time on the current job and total experience separately is that firm-specific experience may have additional effects beyond labor force experience more broadly. Individuals earning more than the taxable maximum report working greater than full time, and especially working 50 or more hours per week, at much higher rates than their counterparts who earn below the taxable maximum. Interestingly, prevalence of high earnings among some groups reporting fewer than 40 hours exceeds that for some full-time groups. This may reflect that some workers with high earnings capability can arrange more flexible work situations. It may also be the result of measurement difficulties, including measurement of part-year and self-employment (Robinson et al. 2011) and norms about reporting working long hours among high earners. Prevalence of high earnings increases with current job tenure at a point in time, but levels off more quickly with the longitudinal measure of any experience over the taxable maximum. Total work experience increases high earnings prevalence, especially for women. For a few cells in this table (for example, among workers with few OASDI work years), the anomaly occurs that the rate for a group ever exceeding the maximum is lower than the group's current rate of exceeding the maximum. Recall that the two computations use different samples, with the latter group restricted to the older members of the sample, so this outcome is theoretically possible if quite rare in practice.

Tables A2.3 through A2.5 repeat these same comparisons, but using a higher earnings threshold, namely 4.5 times the AWI, or approximately $209,200 today (2013). The results are broadly similar, with the differentials among groups generally growing larger. For example, men with a professional degree are about 1.5 times more likely to earn over the taxable maximum than their counterparts with just a bachelor's degree, but they are 5.75 times more like to earn over 4.5 times the average wage. Education gaps for exceeding the taxable maximum are larger among women, but still increase from 5.3 to 6.7 times higher for the more educated when using the higher threshold of 4.5 times the AWI.

Because of confounding between all these characteristics, the appendix also presents some simple descriptive regression analyses.[23] We first present regressions for our standard sample, those workers ages 30 to 67 in the 2004 and 2008 SIPP. We start by using logistic regression to examine whether one's current earnings exceed the cap or the higher threshold of 4.5 times the average wage (table A2.6). These analyses further exclude workers who report fewer than five hours of work in their usual work week to reduce marginal workers' influence.[24]

These regressions reveal a number of interesting patterns. For example, adding job characteristics to the models of whether one earns over these thresholds reduces the effects of most demographic variables, as at a point in time labor force experience is an extremely important correlate of having high earnings. Nativity is one noteworthy exception—the effects of being foreign born tend to increase rather than decline with the addition of job characteristics in the model. One dominant finding from the regression analyses is that effectively all of the differentials that we see in our simple descriptive tables remain statistically significant even after we take into account age and other key characteristics like education, geography, and so forth.

We then use linear regression to examine the natural logarithm of the amount one earned over each of the thresholds (table A2.7). Interestingly, these regression results reveal that demographic and job characteristics better explain these amounts in our model for earners over the taxable maximum than for our model of very high earners. Several variables in the model for earning over the taxable maximum have statistically significant effects, compared to just a few in the model for earnings over 4.5 times AWI. Correspondingly, R-squared is much lower for this latter model. These patterns are in part a function of the modest sample size for the higher earners. In both cases, skill level (as measured by education) and industry appear to be the strongest predictors of earnings level among this subset of high earners.

We also estimate a pooled model that adds observations from a much earlier sample, the 1984 SIPP, and includes interaction terms for being in this earlier panel (table A2.8). We only consider status over the taxable maximum in these regression analyses, given relatively small numbers of cases with earnings over the threshold of 4.5 times the average wage in the 1984 panel in many of the subgroups of interest. These analyses suggest race and gender decline in importance as explanatory factors over time, but education's importance increases between the earlier (1984) and later (2004, 2008) periods (see the interaction terms for the 1984 period). Evidence is also suggestive that location's importance may have increased over time, with metropolitan status more closely tied to probability of earning over the cap, net of other characteristics, in the two later panels. Industry also appears to be more important in the later period than in 1984, as evidenced by the negative coefficients for the 1984 interaction terms for the financial and professional/scientific industries. We suggest cautious interpretation of these results, however, given important changes in the SIPP over this period.[25]

Table 6 presents SIPP estimates of the distribution of earners over the taxable maximum, separately for men and women.[26] For comparability across the SIPP panels, we display the amounts in wage-indexed terms, so each of the lower categories represents an increment of about $2,145 over the cap using the latest values. Figure 4 displays this same information, but cumulatively and using wider categories.

An appendix figure (figure A2.1) similarly shows the distribution of earnings over the taxable maximum in 2011, the latest year for which complete earnings are available, using a more complete sample from SSA data. Figure A2.1 uses absolute rather than wage-indexed dollars but for the full population, as differences for men and women are not available.

The pictures are broadly comparable. Most earners over the taxable maximum earn less than $40,000 over the cap (so their earnings fall below about $150,000 in today's dollars), but a substantial tail of individuals earns very high amounts.[27] Figure 4 shows that men are better represented than women at these very high wage levels, nearly twice as likely to earn 7 or more times the average wage (conditional on earning over the cap), while women are better represented just above the cap.

While we focus on high earnings prevalence because these earnings comprise such a large share of the total, very low earnings also pose important challenges when it comes to the technical matter of projecting lifetime earnings. SSA data reveal that very significant shares of the labor force have very low earnings. For example, Social Security statistics reveal that, in 2011, about 15.6 percent of earners received less than $5,000 in net compensation (SSA undated). Sabelhaus and Song (2009) further highlight that how one treats minimal earnings has first-order effects on the conclusions that one draws about recent trends in earnings volatility. Table 7 therefore provides estimates of who earns low amounts to inform modeling efforts. Our threshold for being a low earner is again a single OASDI-covered quarter. It is clear that these low earners are overwhelmingly young and old. In prime age, around one percent of men with earnings and two to three percent of women earners earn below one quarter of coverage.

Longitudinal earnings, including earnings transitions

We turn now to total experience in the labor force, first examining total years in adulthood worked and then specifically considering high earnings years. We use earnings since 1951 for the analyses of total years of covered work over low thresholds, as these are available reliably. Detailed earnings data are only reliable starting around 1982, so we therefore use just the last 20 years for our analyses of longitudinal continuity among high earners. Table 8 examines cohorts just entering retirement, separately for men and women. In these first analyses, we consider individuals turning ages 60 to 63 in 2010 (the 1947 to 50 birth cohorts).[28] We contrast three separate samples: (1) the full population and then individuals most likely to accumulate a full career's worth of covered earnings—namely, (2) those who were born in the United States or have been in the country since childhood and are not receiving DI benefits, and (3) sample 2, but also excluding those who have worked in uncovered employment for at least one quarter in at least 10 years. We also use four separate definitions of what constitutes a work year—any earnings (top panel), earnings sufficient to earn at least four quarters of coverage from Social Security (the second panel), earnings equivalent to at least half-time, half-year work (520 hours) at the minimum wage (the third panel), and 20 percent of the old-law taxable maximum, equal to about $15,840 in 2011 (the bottom panel).

As table 8 indicates, the majority of men are highly attached to the labor force, with nearly half in these birth cohorts working 40 or more years of at least four covered quarters by age 60. In these cohorts, women are significantly less attached, but still well over a third exceed 35 years of work (the number of years counted toward Social Security benefits in the program's benefit formula) by age 60 using the four covered quarter definition of a work year. The estimates in the samples with the two less stringent work years definitions are quite sensitive to whether one includes disabled workers, immigrants, and uncovered workers, with shifts of 4 to 6 percentage points for women and 8 to 11 percentage points for men in the overall share earning 40 or more years. For example, over 59 percent of men have worked 40 or more years using the four covered quarters definition and excluding DI beneficiaries, immigrants, and uncovered workers, compared to 48 percent when we do not make these exclusions.

Table 9A describes how earnings levels, defined here as the average of the two highest earnings years in one's work history, relate to total work years. [29] These relationships are important given that a number of proposals to modify Social Security that target certain benefit adjustments and exemptions on the basis of work years. The table reveals that while most relatively high earners (for example, those earnings more than 1.5 times the AWI) have worked 40 or more years by age 60, lower earners are not as closely bunched at the bottom of the work years distribution. Significant shares of low-maximum earnings workers, especially men, do work 40 years by age 60. Other research shows the characteristics of long-service, low-wage workers (e.g., Favreault 2010).

Table 9B similarly looks at how permanent earnings and work years relate to one another. This time, our earnings measure covers a longer period, the 35 years in Social Security's Average Indexed Month Earnings (AIME) calculation. In computing AIME, we assume that all workers would claim benefits at age 62. We then divide the AIME estimate by poverty, specifically the non-aged poverty level for a single person from the U.S. Census Bureau.[30] We use this metric because prior proposals have referenced it, for example, as a way for defining eligibility for exemption from retirement age increases as part of the National Commission on Fiscal Responsibility and Reform (NCFRR) (2010) proposal, better known as the "Simpson-Bowles" Commission proposal. Because we focus on earnings through age 62, we look at slightly older cohorts than in table 9A (1945 to 1948, compared to 1947 to 1950). Once more, we exclude DI beneficiaries and those immigrating to the U.S. as adults from the table to get a better sense of these patterns for retired workers at risk of a full career of earnings.

Men are concentrated in the cells with at least 25 work years and high earnings (at least 250 percent of poverty). Women are concentrated in the cells with comparatively lower earnings, but more evenly distributed by work years. For both men and women, having high earnings and fewer than 25 work years is exceedingly rare. Of policy significance, we see that in recent cohorts women workers would be more likely to qualify for a hardship exemption under the NCFRR plan than men. In total, around 10 percent of men and 23 percent of women would have been potentially eligible for the full exemption in recent cohorts.

Table 10A describes twenty-year experiences with the taxable maximum, separately by gender and age to better isolate duration at risk of being over the cap. While most never exceed the taxable maximum and many of those who do exceed it earn over the cap just one or two years, a substantial minority, especially among men, earns over the cap at least half the time. For example, among men age 50 to 59, nearly half (47 percent) earned over the taxable maximum for at least 10 years and nearly one third (31 percent) earned over the maximum for at least 15 years). Close to a third (32 percent) of the women in that same age range exceeded the taxable maximum for at least 10 years. Table A2.9 provides this same information, but again using the higher threshold of 4.5 times the AWI. While the share of individuals crossing the threshold is much lower at this higher earnings level, the dynamic is somewhat similar, with the mode crossing the threshold just once, but about a quarter crossing it for at least eight years.

Table 10B presents similar data from another perspective. We examine this same distribution, but in 2010. Instead of looking at the last 20 years, we consider the last 28 years, the longest interval our data permit. This longer look back has significant advantages, allowing us to further disaggregate individuals with many years of experience over the taxable maximum into a group with 20 or more years.

There are some disadvantages as well. First, the data may be somewhat less representative, especially at younger ages, because they do not capture immigrants after the SIPP follow-up period. Also, the last several years we examine are recessionary ones, so the point in the business cycle may overly influence patterns at younger ages. Our main conclusion from this table is that the results are strikingly similar to the prior table. Strong concentrations of workers earn over the maximum for a small number of years, and then a second concentration spends extended parts of the career over the maximum.

An examination of the longitudinal characteristics of low earnings (not shown) for prime age workers revealed far less persistence. Most ages 35 to 55 never earned a very low amount (greater than zero but less than one covered quarter).[31] The small share that did usually did this just once or twice over a twenty-year period.

Table 11 further illustrates the dynamics for these high earners. It shows entry and exit rates for those earning above the taxable maximum and describes spell lengths for those with multiple spells.[32] At a point in time, only about one percent of workers who were earning below the taxable maximum last year exceed it this year, while about 84 percent of workers who did earn above the taxable maximum last year earned above it this year. The odds of remaining above the cap vary directly with the amount of time one has been earning over the cap, with over 90 percent of those over the maximum for six or more years remaining there, compared to 60 percent for those who have only been over the maximum for one year. Education also appears closely tied to the chances of moving over the maximum and staying there. For example, those with a professional degree are more than twice as likely to enter and only about half as likely to exit when compared to their counterparts with only a bachelor's degree.

An important challenge of modeling lifetime earnings is that while developers need to accurately reproduce the cross sections and total number of earnings years, they must also consider how earnings evolve over time. The OASDI benefit formula is sensitive to the order in which one accrues earnings and other factors, like the age at which one earns a given amount. We therefore next report transition matrices to better understand how earnings evolve. This approach is consistent with analyses by CBO (2006), which consider how earnings in a given year relate to lifetime earnings for those ages 50 to 60.

We begin with relatively short-run transitions. Table 12 displays earnings quintile transitions from the average of the past five years to this year separately for men and women in prime age (namely, 35 to 59).[33] We display row percentages (i.e., each row adds to one hundred percent). These analyses include data from more SIPP panels than the prior estimates to ensure reliable estimates of the cells where transitions are relatively rare (e.g., movements from the lowest to the highest quintile or the reverse). Consistent with prior estimates, these matrices reveal a tendency for individual earnings to remain relatively stable. For example, about 83 percent of men in the top quintile stay there, and about 65 percent in the bottom remain. Interestingly, the men's and women's matrices are similar, though the quintile breaks differ (they are much broader for men than for women).

Tables 13 show transitions to current earnings from earnings over a longer period, a ten-year average of prior earnings. The conditions that we impose to be included in this sample are different than for the five-year transitions, where we only require that one had earned at least one dollar in three of the last five years. Here we similarly require one to have been an earner in more than a majority of years (so six years in the case of these ten-year transitions). We also expand the age range further, from 30 to 64. These matrices suggest more mobility between quintiles over longer horizons, especially for women.

Implications of Earnings Patterns for Benefit Levels under Current Law and Alternatives

We next try to understand how these patterns of lifetime earnings mobility shape OASDI benefit accruals under current law and how this might change with changes to the payroll tax along the lines proposed by various policymakers. Our first step is to compute Primary Insurance Amounts (PIAs) accrued to late career under current law.[34] We then compute earnings that would be taxed and the resulting PIAs if the earnings and benefit base were raised to various levels or uncapped altogether. This reveals where along the benefit formula the earnings lie. We compute these measures on an individual basis for those married at the time of the survey, ignoring spouse and survivor entitlements for simplicity's sake.

Figure 5 displays how Social Security's benefit formula works under current law, with average indexed earnings displayed on the left vertical axis, PIA along the horizontal axis, and replacement rate (the ratio of PIA to AIME) along the right vertical axis. Examining the figure, we can see that the marginal rate that individuals receive on their additional payroll tax contributions is distinct from their replacement rate. For example, those who had earned just shy of the taxable maximum for the highest 34 years of their career would be earning 15 percent on their new earnings in the 35th year, but receiving a replacement rate of closer to 30 percent, as some of their lifetime earnings fall in the 90 and 32 percent brackets under the current formula.

Tables 14a and 14b start with analogous worker replacement rates for men and women, respectively, from cohorts entering retirement today, specifically, those born between 1941 and 1947, so reaching ages 63 through 69 by 2010. This replacement rate calculation accounts for neither heterogeneity in actuarial reductions nor income taxes paid on OASDI benefits.[35] We compare these replacement rates under three alternative sets of assumptions: (1) current law scheduled; (2) assuming that the taxable maximum is removed retrospectively in 1983, and workers earn benefits under the current formula on the additional earnings; and (3) assuming that the taxable maximum is removed retrospectively in 1983, and workers do not earn benefits under the current formula on the additional earnings.[36] These estimates provide a lower bound of the effects of removable of the taxable maximum in the future because of censoring of earnings over the taxable maximum until 1983 in our data. But they can provide an important illustration of some of the longitudinal properties of high earnings and how they would play out under proposals to remove or increase OASDI's contribution and benefit base.[37] We would expect that future cohorts, and especially future cohorts of women, would have different experiences (see, for example, Wu et al. 2013).

We specifically show deciles of the replacement rate distribution, and look separately at those workers who have and have not earned over the taxable maximum over the course of their careers. For those workers earning over the taxable maximum, we differentiate those with more years of experience from those with limited experience, using different classifiers for men and women (ten and five, respectively) given relatively few women with many years over the maximum.

Bear in mind that the *low* replacement rate deciles generally correspond to *high* lifetime earners and the *high* deciles to *low* lifetime earners because of the benefit formula's progressivity.[38] We see that the median male worker in these cohorts can expect a replacement rate of around 43 percent under current law scheduled, not accounting for actuarial reductions for early claiming. The median female worker, who may receive benefits as a spouse or survivor (here we focus on potential returns to their own work), can expect a rate of 57 percent, again before actuarial reductions. Workers with experience over the taxable maximum have median rates that are about 8 percentage points lower for men (35 percent) and 17 percentage points lower for women (40 percent). The median for men with 10 of more years over the maximum is about 2 percentage points lower than for all men who ever earn over the cap, so 33 percent. For women with five or more years of experience the rate is about 3 percentage points lower than for all women ever over the cap, so 37 percent.

When we remove the cap retrospectively starting in 1983 but allow benefits to be paid on all the additional earnings, the replacement rate for the median man earning over the maximum drops about one percentage point (from 35 percent to 34 percent). However, the rate for the man in the lowest decile with any experience over the maximum will drop by 7 percentage points (from 32 percent to 25 percent). For those with 10 or more years of experience over the maximum, the drop is 10 percentage points (from 32 to 22). When we remove the cap and do not allow benefits to be paid, we find that the lowest decile of those earning over the maximum at least once declines by 13 percentage points relative to current law scheduled (from 32 to 19). For those over the cap for 10 or more years, the drop in the bottom decile is 19 percentage points (from 32 to 13). The median for those men earning over the cap, in contrast, drops just 2 percentage points under this option.

An important overall conclusion from these simple calculations is that the skewed distribution of experiences over the taxable maximum which we described earlier has important implications for returns from OASDI under alternative proposals. Many who would be affected by policies that would raise or remove the taxable maximum would experience relatively modest changes in their replacement rates because they earned over the maximum in just a few years or their earnings over the maximum were only modest. A minority, presumably those with many years over the maximum and earnings that more substantially exceeded the maximum, could experience fairly deep reductions in their replacement rates depending on how the newly covered earnings counted toward benefits. However, these analyses are just a preliminary look. More complete distributional analyses must also figure in effects on spouse and survivor benefits and consider the possibility of behavioral response by workers.

Projection Results

Comparing projected MINT earnings with historical earnings

To evaluate the MINT projections, we focus on the projections of future earnings rather than past earnings. The MINT starting sample closely reflects the matched data, which we use for evaluation, so the historical comparisons are extremely close and thus not informative.[39] For our analyses of aggregate measure, we use a broad time series. For more detailed individual level characteristics, we focus on the earnings distribution at several points in time: 2020, 2040, and 2060.

An important objective is to determine whether the projections significantly deviate from historical patterns and whether these differences might indicate specification problems. Some deviations are to be expected, of course. When dealing with relatively small subsets of the population at a single point in time, sampling variation alone will result in some differences. Further, some changes to patterns might make sense given other trends. For example, women's increasing education suggests that in the future they may be more likely to earn over the taxable maximum than they are at present, and men's declining relative education may suggest future declines in their share. Increased inequality in earnings could have important implications for the share of people who ever earn over the maximum in a career and for the number years over the maximum for those who exceed it at least once.

Starting at the top of the distribution, we examine first the share of covered workers earning over the taxable maximum, by gender (figure 6). The forecast suggests something of a continuation of the trend in the cross-sectional pattern revealed in figure 2. Women become more likely to earn over the taxable maximum and men less likely, leading to a relatively stable prevalence of earners over the maximum.

Looking more comprehensively at the earnings distribution, figures 7a through 7e shows deciles of wage-indexed earnings in MINT from 2007 through 2050 for men (7a and 7b), women (7c and 7d), and all workers (7e and 7f). For each group, the first graph shows all deciles plus the 5th, 95th, and 99th percentiles. The second graph looks more narrowly at the bottom half of the distribution using a smaller scale so patterns will be more readily visible. As 2010 is the last year of historical data, all other values are projected.

Generally, these figures suggest a relatively stable earnings distribution in wage-indexed terms, which implies growth in real terms. Consistent with the pattern for earnings over the taxable maximum, the men's earnings tend to decline somewhat at some of the percentiles, while women's tend to increase. At the median, we do see a net decline in overall wage-indexed earnings when taking into account these offsetting factors.

We also look again at the distribution of years over the taxable maximum over the last 20 years, both the share of individuals who do not exceed the cap over the period (table 15) and the distribution of total years above the cap for those who do exceed the cap at least once (table 16). We see that from age 45 onward, in 2020, 2040, and 2060, relative to the past women are less likely to have zero years over the taxable maximum, while men are more likely (table 15). The women's decline, however, does not offset the men's increase. As in the historical period, numbers of spells over the taxable maximum tend to be somewhat bimodal for workers with substantially complete careers (for example, workers ages 60 to 67). Significant shares of people earning over the cap just once (around 17 to 20 percent for men and 21 to 22 percent for women in their late 60s), and nearly 40 to 45 percent of men and 28 percent increasing to over a third of women earning over the cap for at least 10 of the 20 years (table 16). This suggests declining concentration at higher numbers of years for men and increasing concentration for women, a pattern worthy of deeper investigation.

We next evaluate the transition matrices for the model population as a whole, again considering outcomes in 2020, 2040, and 2060. Tables 17 and18 compare five-year and ten-year transitions, respectively. We focus once more on prime age and examine transitions separately for men and women. The matrices reveal striking persistence. Once more, the shares of individuals who stay in the quintile they occupied last year (i.e., the "diagonals") are quite high, especially the cells that represent transitions from high earnings to high earnings. For both men and women, typically about 80 to 81 percent of those in the highest earnings quintile over the past five years are high earners again in the next. (This is a bit lower than our estimate for staying above the higher threshold of the taxable maximum, where close to 83 percent remained above the threshold in the historic period.)[40] Looking back 10 years, this falls to closer to 75 percent, but is still persistent. Across the projection years, the matrices are quite stable, and differences between the men's and women's matrices are generally quite small, except in the ten-year transition matrices, where women exhibit significantly more mobility out of the bottom quintile than men do in earlier years (2020 especially), again consistent with the historical experience. When comparing these projected MINT matrices to the historical estimates from SIPP, MINT appears to line up quite well over both the five- and ten-year periods.

Conclusions

Our descriptive analyses of the SIPP data reveal a U.S. labor force that is highly stratified on the basis of demographic and job characteristics. The data also suggest that individual rankings in the earnings distribution are persistent over the life course. We find that a large group has earnings that exceed the taxable maximum just once over the last 20 years, and most workers earning over the taxable maximum earn less than $40,000 above the cap. Nonetheless, a substantial minority of higher earners exceeds the cap for more than 10 years, and aggregate data from other sources reveal that very high earners are garnering an increased share of earnings over the cap. Further, earnings stability is quite strong in the highest quintile over two accounting periods.

Preliminary results suggest that MINT captures these patterns reasonably well in future periods. The model does project a decline in median wage-indexed earnings, a change that may be driven by the influence of the recent, deep recession on long-range outcome. These patterns are worthy of monitoring and further exploration given great uncertainty about labor conditions for the future.

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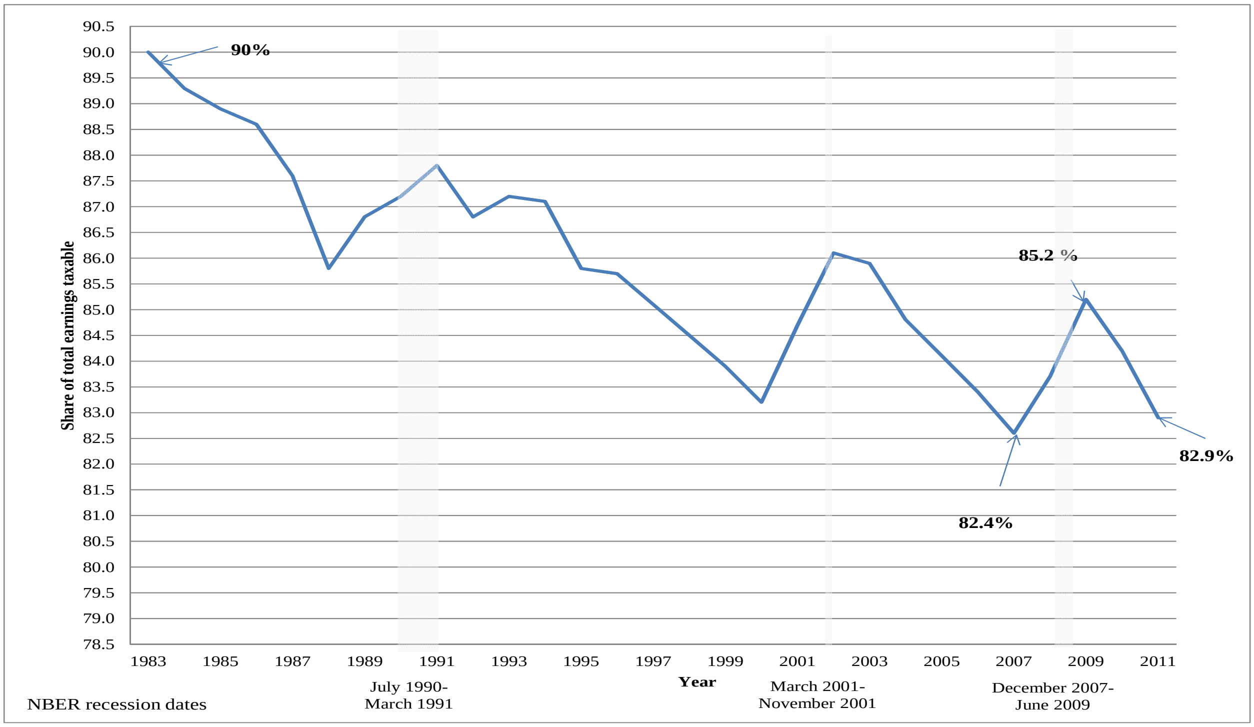
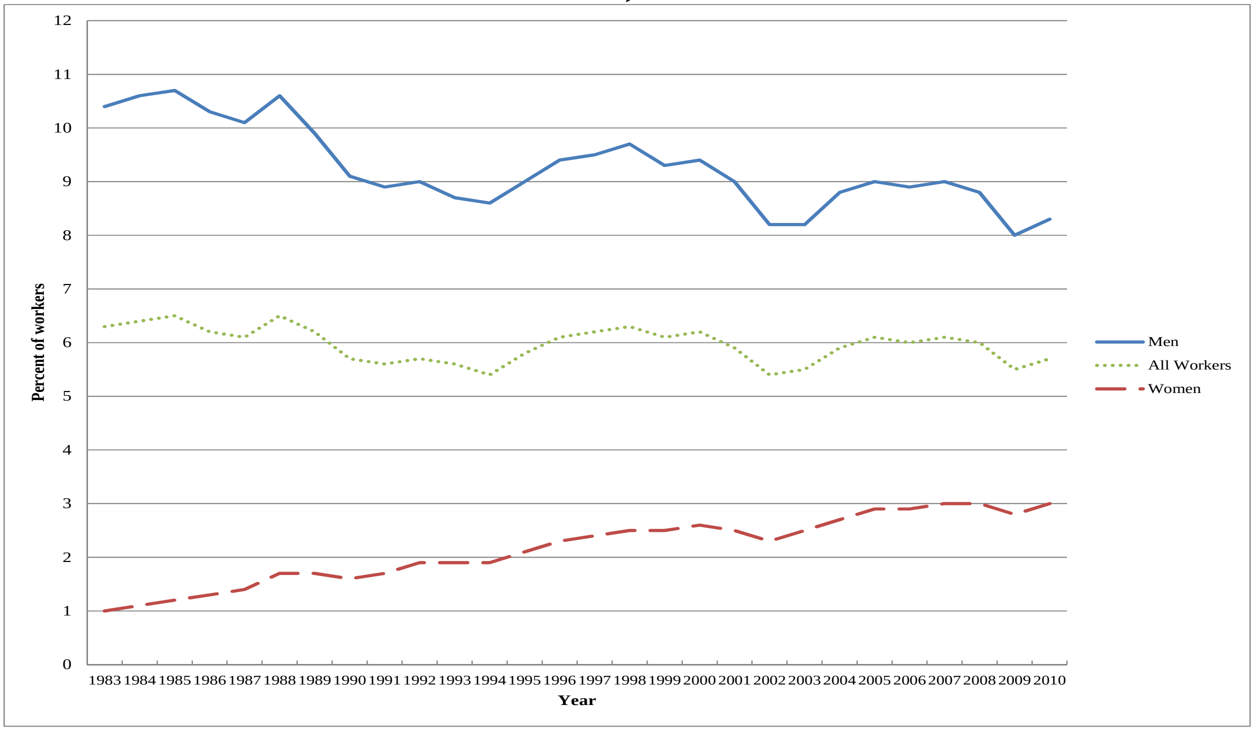
Figure 1. Historical Values of the Taxable Share, 1983 to 2011



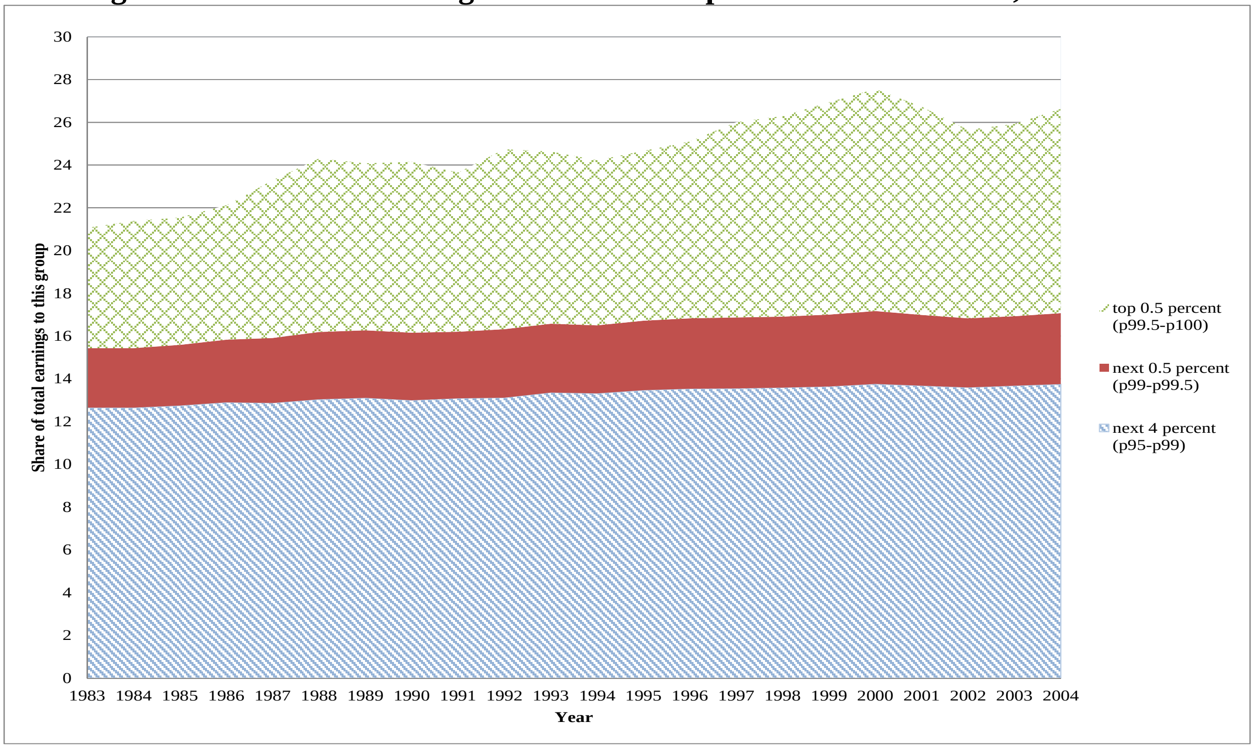
Source: Table 4.B1 *Annual Statistical Supplement to the Social Security Bulletin*.
Notes: Data for years 2008 through 2011 are preliminary. NBER = National Bureau of Economic Research.

Figure 2. Share of All Covered Workers with Earnings above the Taxable Maximum, by Sex and Year, 1983 to 2010



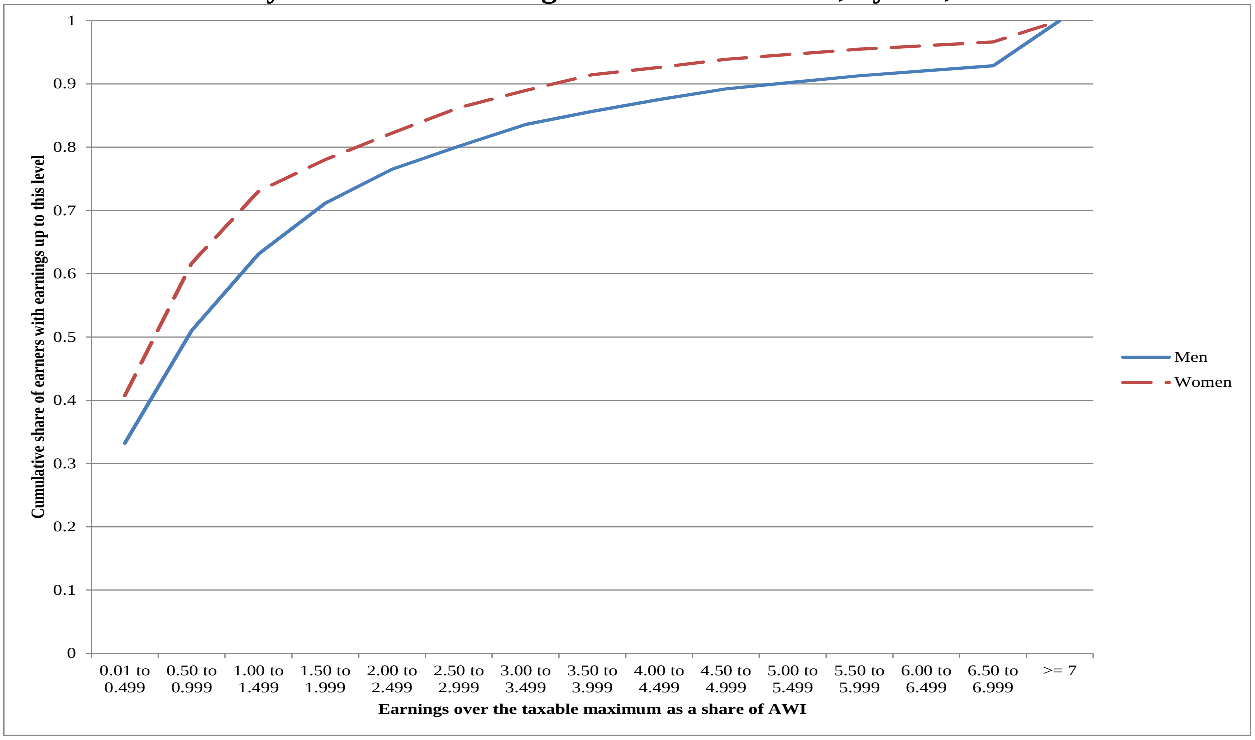
Source: Table 4.B4 *Annual Statistical Supplement to the Social Security Bulletin*.
Notes: Data for years 2008 through 2010 are preliminary.

Figure 3. Growth in Earnings Share of the Top 5 Percent of Earners, 1983–2004



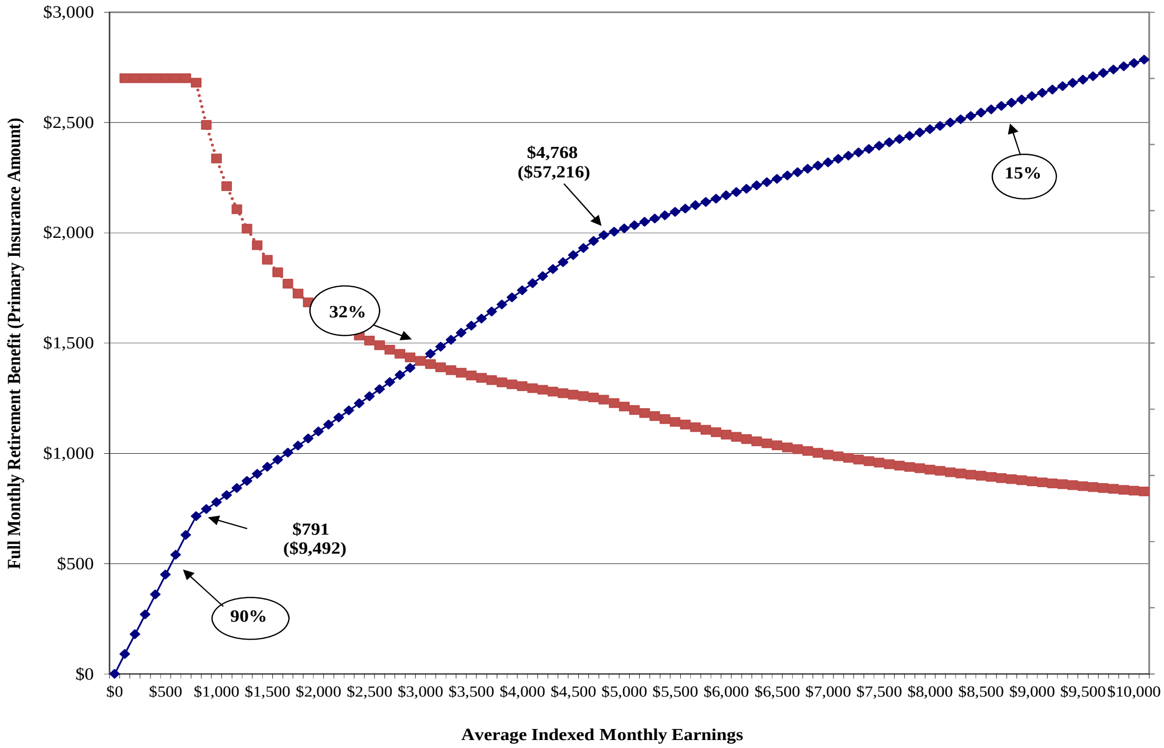
Source: Table A3 from Kopczuk et al. (2007).

Figure 4. Cumulative Distribution of Earners at All Ages with Earnings over the Taxable Maximum by Amount of Earnings over the Maximum, by Sex, 2004 and 2009



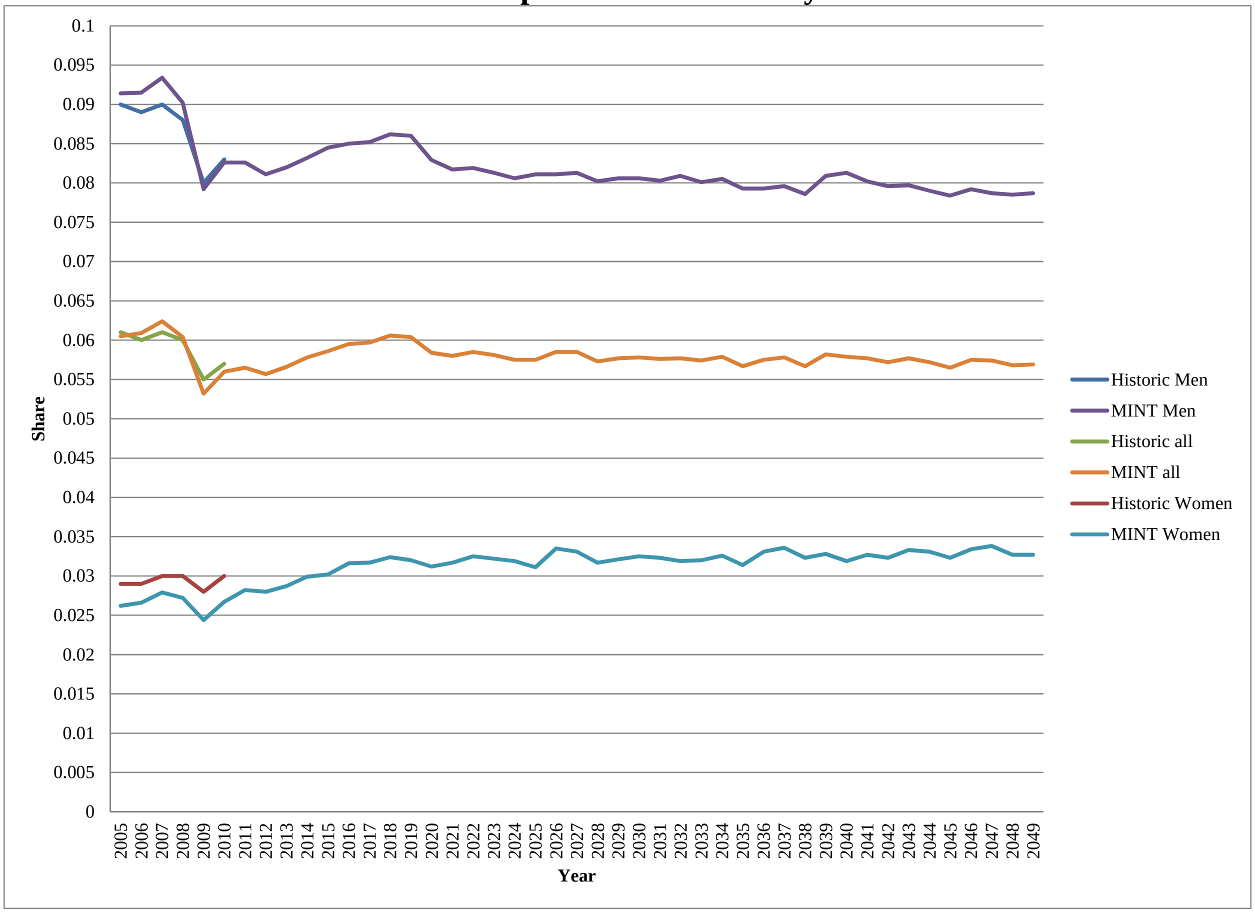
Source: Authors' calculations from SIPP matched to DER, SER and Numident (table 6). Sample weights account for relative probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants. Notes: Values for 5.0 to 5.49 and 6.0 to 6.49 are linearly interpolated from neighboring points to maintain adequate sample sizes.

Figure 5. Social Security Benefit Formula, 2013 with Replacement Percentages (in circles) and Bend Points (Annualized Values in Parentheses) and Corresponding Replacement Rates (PIA/AIME) (Axis on right)



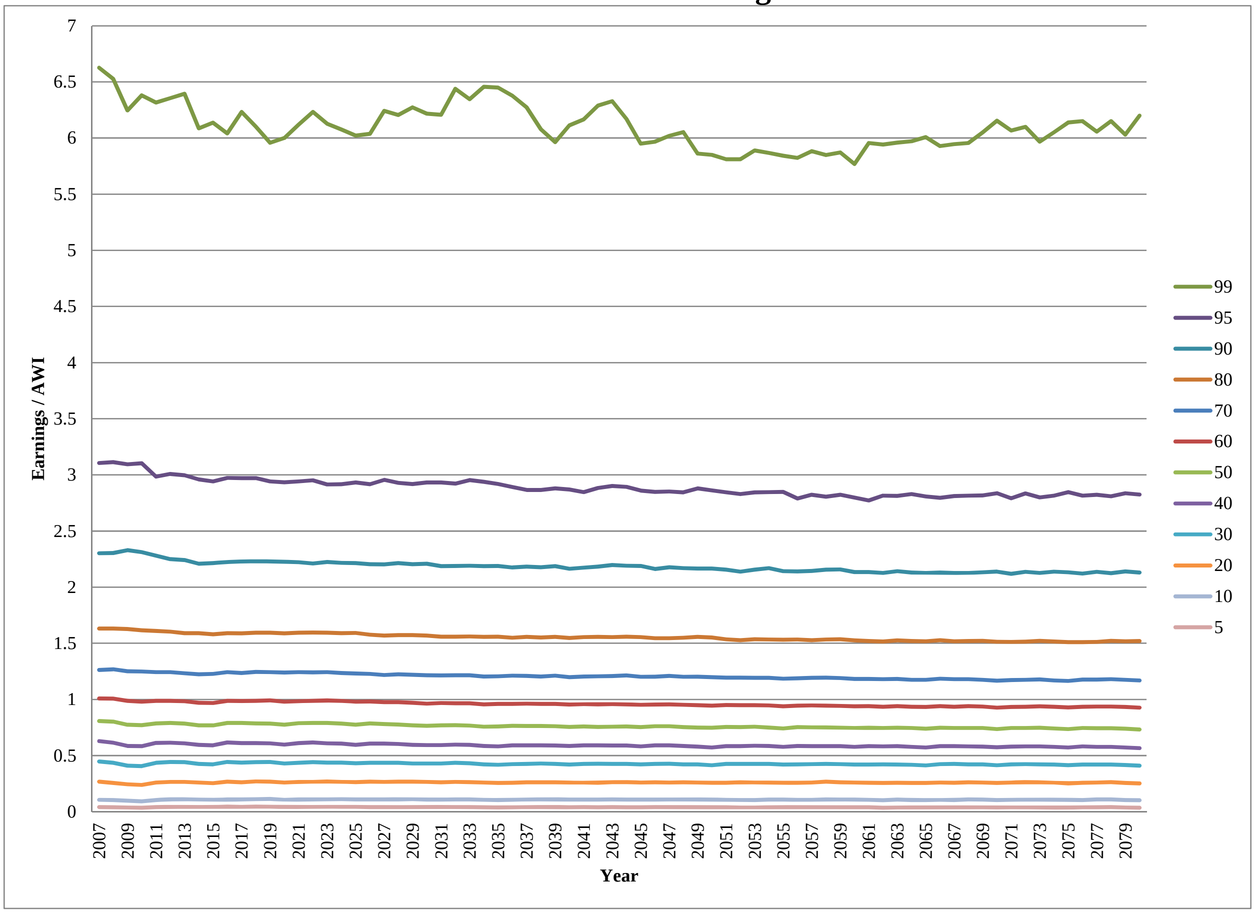
Source: Social Security law.
Notes: Monthly value of taxable maximum for 2013 is $9,475.

Figure 6. Percentage of Covered Workers with Earnings over Maximum Taxable: MINT Compared to Historical by Year



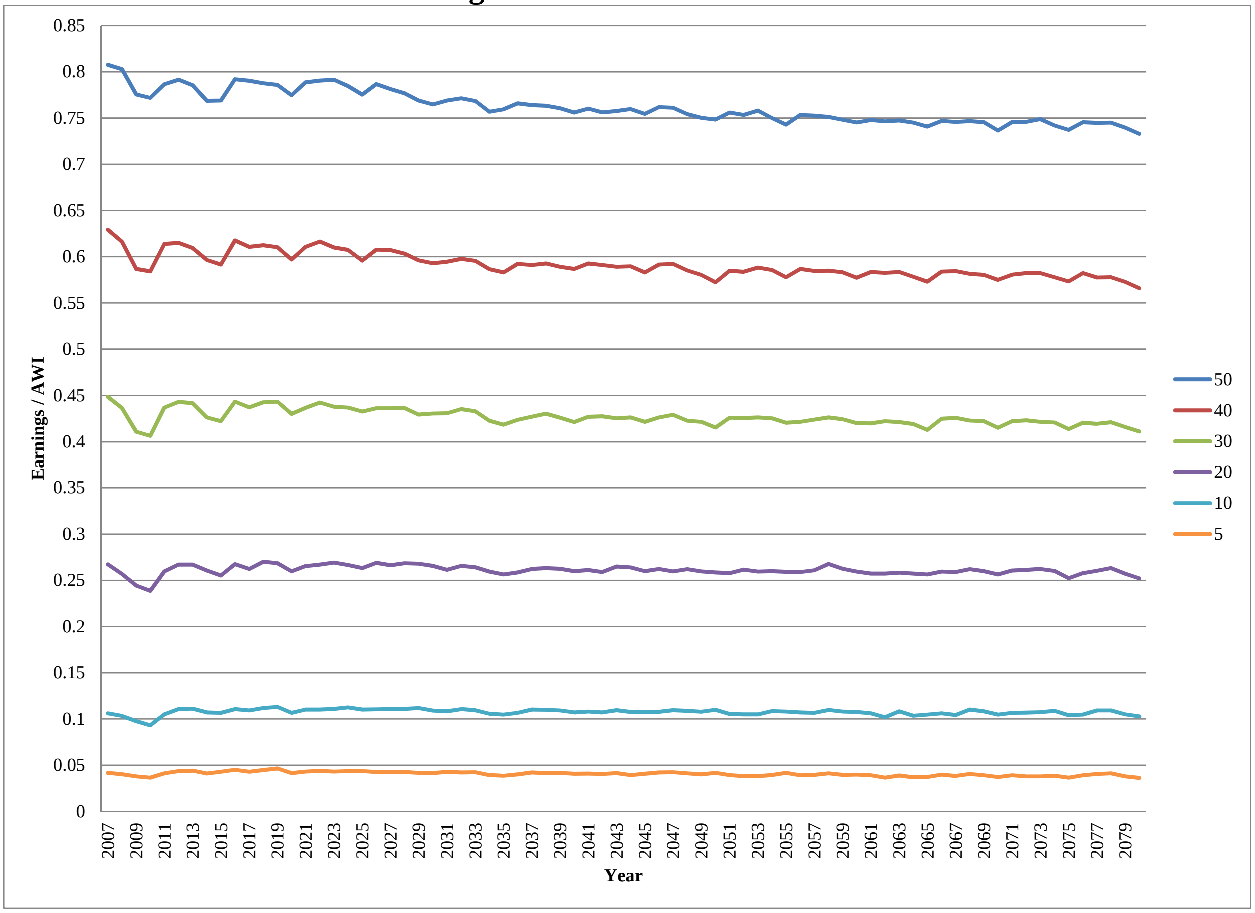
Sources: Table 4.B4 in *Annual Statistical Supplement* (Social Security Administration 2012a) and authors' computations from MINT7 (dated July, 2013).
Note: MINT sample does not include individuals born prior to 1926, so early years of this figure are missing a small number of earners ages 75 and older.

Figure 7a. Percentiles of Total Wage-Indexed Earnings in MINT7, by Year: All Men with Earnings



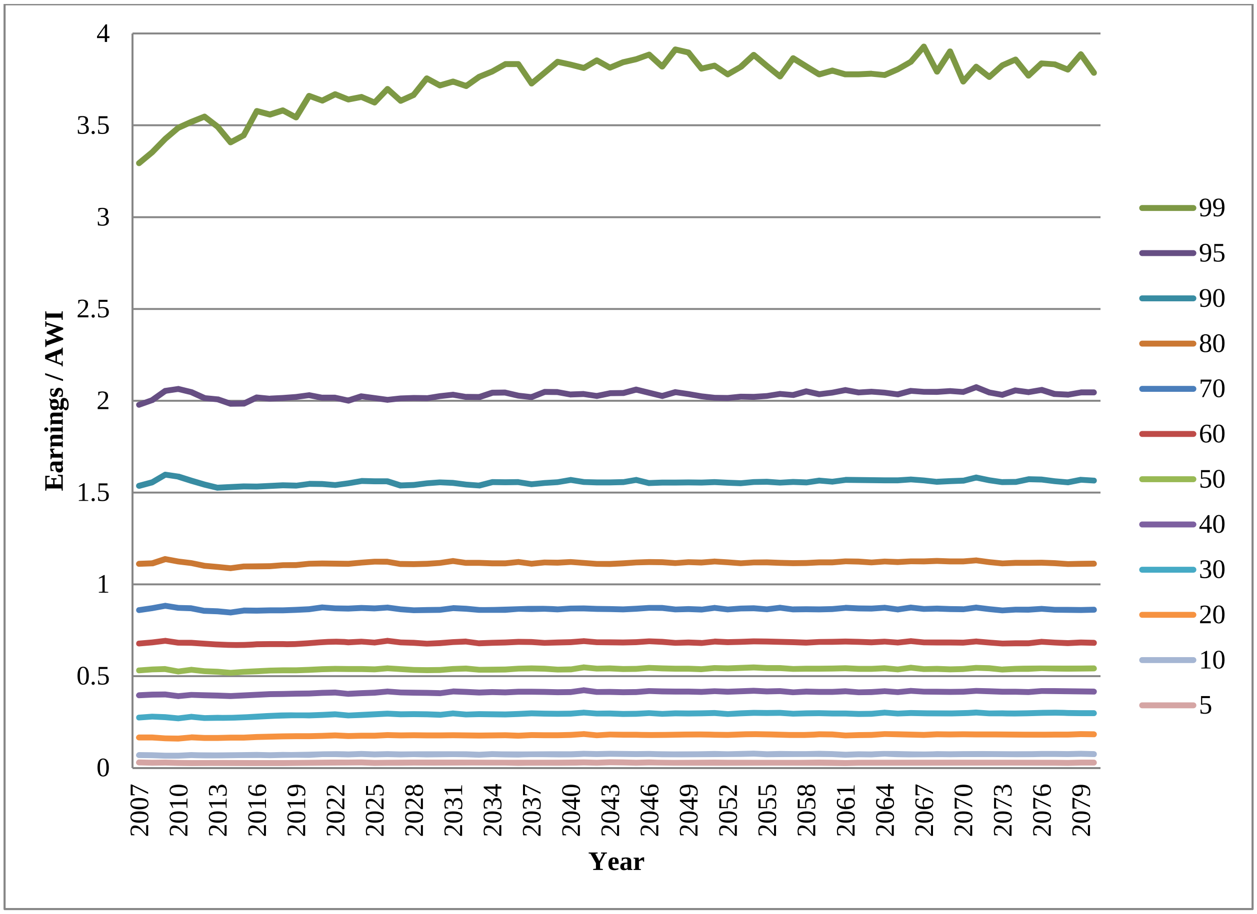
Sources: Authors' computations from MINT7 (dated July, 2013).
Note: MINT sample does not include individuals born prior to 1926, so early years of this figure are missing a small number of earners ages 75 and older.

Figure 7b. Percentiles of Total Wage-Indexed Earnings in MINT7, by Year: Men with Earnings in the Bottom Half of the Distribution



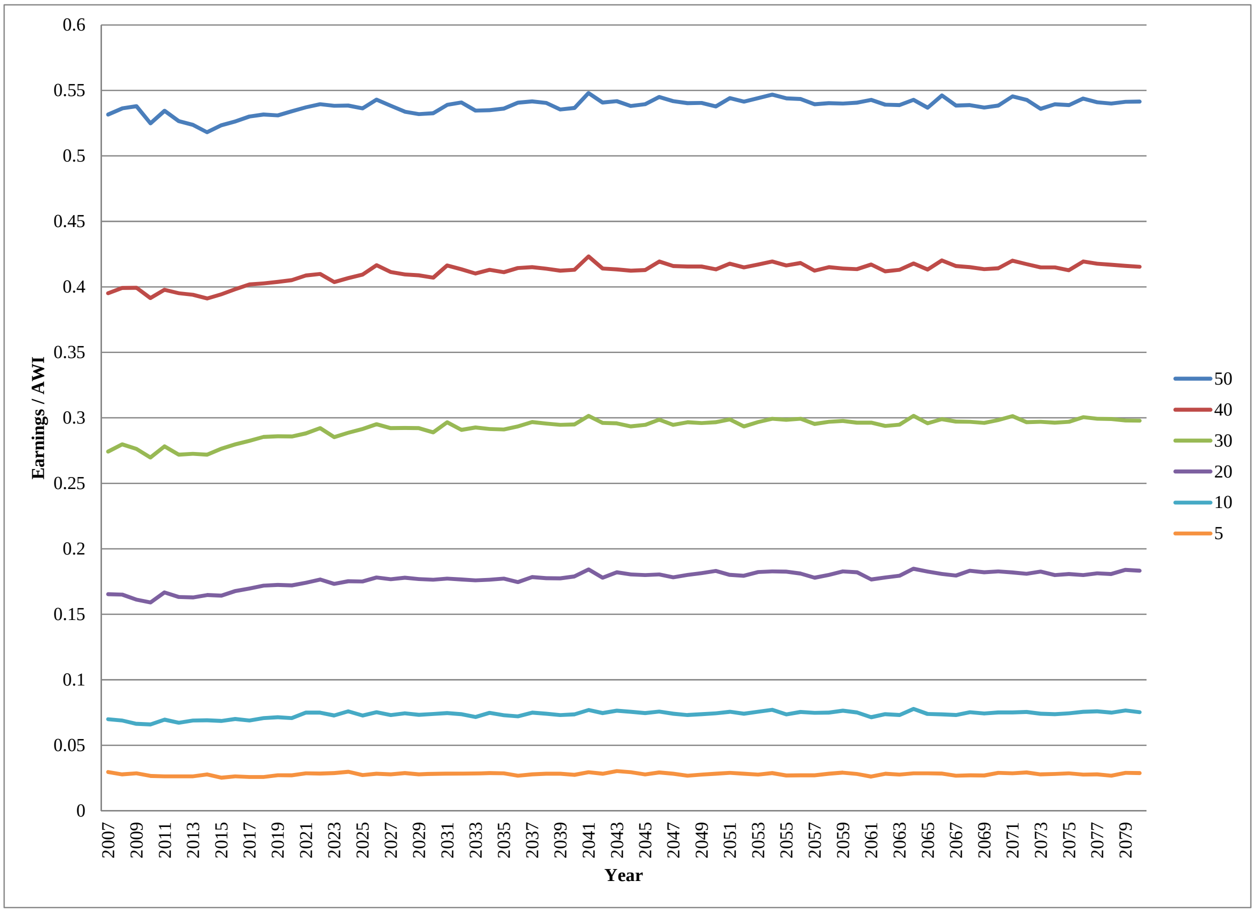
Sources: Authors' computations from MINT7 (dated July, 2013).
Note: MINT sample does not include individuals born prior to 1926, so early years of this figure are missing a small number of earners ages 75 and older.

Figure 7c. Percentiles of Total Wage-Indexed Earnings in MINT7, by Year: All Women with Earnings



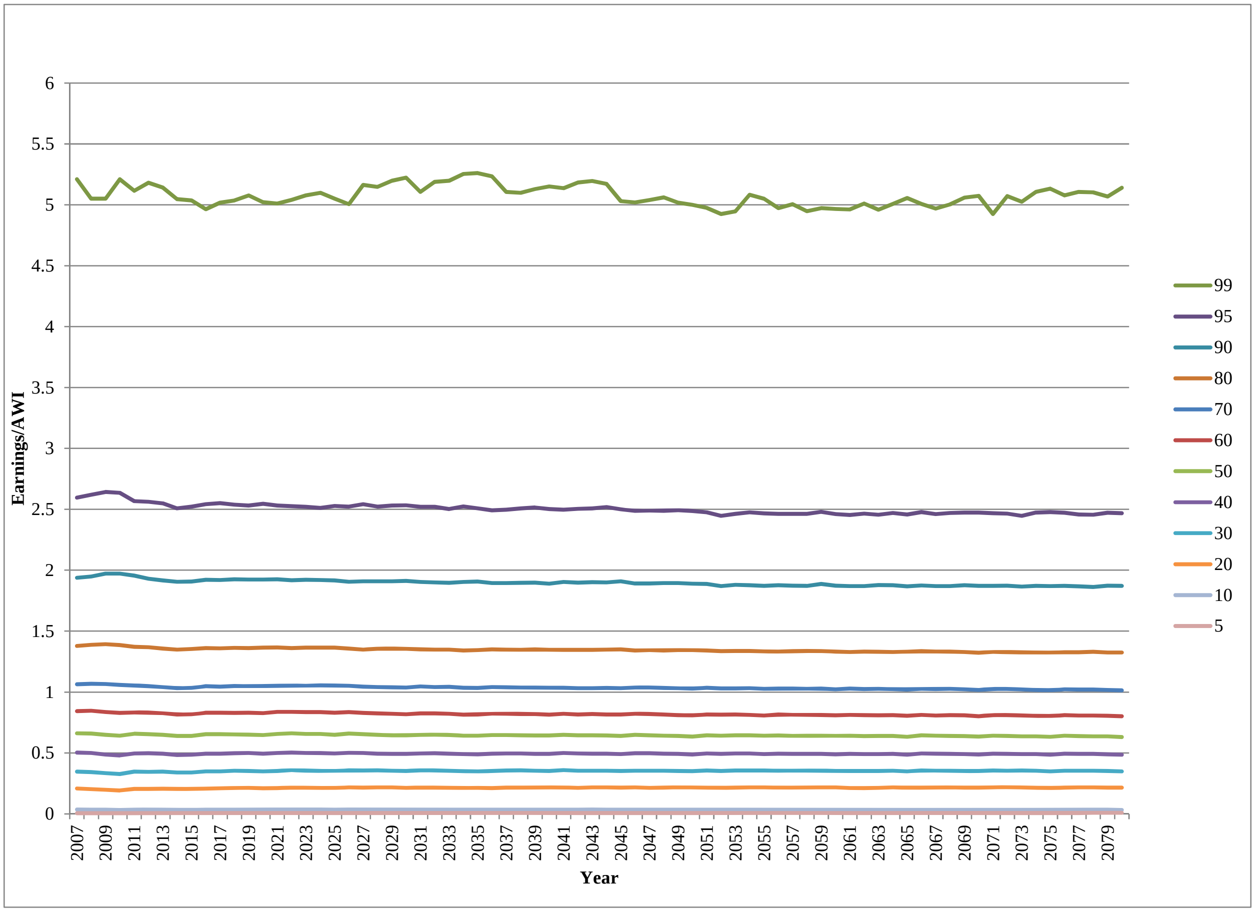
Sources: Authors' computations from MINT7 (dated July, 2013).
Note: MINT sample does not include individuals born prior to 1926, so early years of this figure are missing a small number of earners ages 75 and older.

Figure 7d. Percentiles of Total Wage-Indexed Earnings in MINT7, by Year: Women with Earnings in the Bottom Half of the Distribution



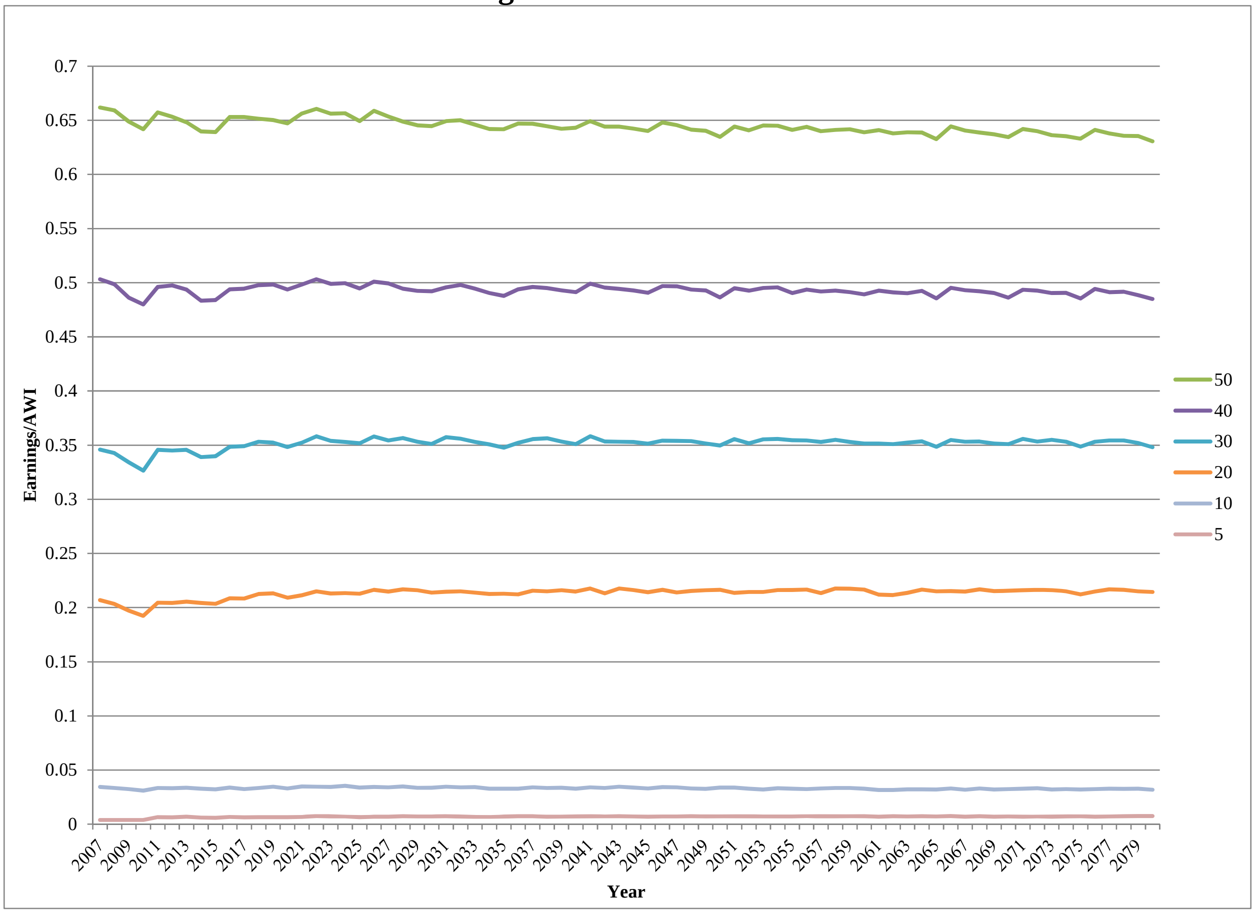
Sources: Authors' computations from MINT7 (dated July, 2013).
Note: MINT sample does not include individuals born prior to 1926, so early years of this figure are missing a small number of earners ages 75 and older.

Figure 7e. Percentiles of Total Wage-Indexed Earnings in MINT7, by Year: All Workers with Earnings



Sources: Authors' computations from MINT7 (dated July, 2013).
Note: MINT sample does not include individuals born prior to 1926, so early years of this figure are missing a small number of earners ages 75 and older.

Figure 7f. Percentiles of Total Wage-Indexed Earnings in MINT7, by Year: Workers with Earnings in the Bottom Half of the Distribution



Sources: Authors' computations from MINT7 (dated July, 2013).

Note: MINT sample does not include individuals born prior to 1926, so early years of this figure are missing a small number of earners ages 75 and older.

Table 1. Shares of Individuals with Earnings (Using Two Definitions of Earners) over Taxable Maximum in 2004, 2009 by Age and Sex

Age	Men		Women		All	
	Any	> = 1CQ	Any	> = 1CQ	Any	> = 1CQ
0–29	0.008	0.010	0.004	0.004	0.006	0.007
30–34	0.063	0.072	0.028	0.031	0.046	0.053
35–39	0.104	0.120	0.033	0.037	0.071	0.081
40–44	0.121	0.133	0.036	0.040	0.080	0.088
45–59	0.124	0.139	0.040	0.045	0.083	0.093
50–54	0.127	0.140	0.040	0.043	0.084	0.092
55–59	0.124	0.136	0.036	0.038	0.082	0.088
60–64	0.106	0.118	0.022	0.025	0.066	0.074
65 plus	0.050	0.063	0.011	0.014	0.033	0.041
All	0.079	0.093	0.025	0.029	0.053	0.062
N	54,685	44,367	52,603	43,826	107,288	88,193

Source: Authors' calculations from SIPP. "Any" column uses matched SER data where available and SIPP self–reports where not. "Greater than 1 CQ" column describes individuals who match to SER and DER, using SER data to determine whether one's earnings crossed the one covered quarter threshold.

Table 2. Shares of Individuals Earning over the Taxable Maximum, by Demographic Characteristics: Workers Ages 30 to 67 at a Point in Time (2004, 2009) and All Individuals Ages 45 to 67 over the Last 20 Years

Characteristic	Shares over taxable maximum					
	Men		Women		All	
	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)
All	0.114	0.271	0.035	0.073	0.076	0.168
Age						
30–34	0.068*	n/a	0.029*	n/a	0.049*	n/a
35–39	0.113*	n/a	0.034*	n/a	0.076*	n/a
40–44	0.125	n/a	0.038	n/a	0.083	n/a
45–49 (REF)	0.131	0.230	0.042	0.076	0.087	0.151
50–54	0.131	0.266*	0.040	0.082	0.087	0.171*
55–59	0.125	0.285*	0.036	0.076	0.082*	0.176*
60–64	0.105*	0.314*	0.022*	0.066	0.066*	0.185*
65–67	0.074*	0.296*	0.015*	0.047	0.047*	0.163*
Education						
Less than high school	+	0.051*	+	0.005*	+	0.027*
High school grad/GED or less	0.022*	0.136*	0.005*	0.022*	0.014*	0.074*
Some college	0.055*	0.221*	0.013*	0.052*	0.034*	0.131*
College graduate (REF)	0.209	0.455	0.063	0.144	0.139	0.298*
Masters degree	0.287*	0.529*	0.084*	0.188*	0.183*	0.350*
Professional degree	0.532*	0.764*	0.334*	0.436*	0.462*	0.654*
Doctoral degree	0.409*	0.673*	0.251*	0.402*	0.352*	0.582*
Race/ethnicity						
Non-Hispanic white (REF)	0.134	0.311	0.039	0.081	0.089	0.193
Non-Hispanic black	0.036*	0.122*	0.020*	0.051*	0.027*	0.082*
Non-Hispanic Asian/Pacific Islander	0.179*	0.273*	0.088*	0.126*	0.134*	0.194
Non-Hispanic Native American	0.056*	0.146*	0.016*	0.037*	0.037*	0.088*
Hispanic	0.037*	0.099*	0.011*	0.024*	0.025*	0.060*
N	34,403	23,645	33,771	26,852	68,174	50,497

Source: Authors' calculations from SIPP matched to DER, SER, and Numident. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants.
Notes: "+" indicates combined with the row below for this analysis to maintain adequate sample sizes.
"*" indicates prevalence statistically differs from the reference group (denoted by "REF") for this row and column at p<0.05 level.

Table 3. Shares of Individuals Earning over the Taxable Maximum, by Nativity, Family Demographic Characteristics, and Geography: Workers Ages 30 to 67 at a Point in Time (2004, 2009) and All Individuals Ages 45 to 67 over the Last 20 Years

	Shares over taxable maximum					
Characteristic	Men		Women		All	
	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)
Nativity						
Native–born (REF)	0.116	0.281	0.034	0.075	0.076	0.174
Foreign born, MDC	0.189*	0.336*	0.062*	0.080	0.126*	0.200*
Foreign born, LDC	0.074*	0.144*	0.034	0.054	0.056*	0.097*
Marital status (current)						
Married spouse present (REF)	0.137	0.315	0.036	0.073	0.091	0.195
Married spouse absent	0.113*	0.254	0.039	0.064	0.078*	0.161
Widowed	0.058*	0.166*	0.021*	0.044*	0.029*	0.069*
Divorced or separated	0.059*	0.177*	0.030*	0.077*	0.043*	0.120*
Never married	0.056*	0.121*	0.040	0.095	0.048*	0.108*
Number of children ever born						
None	0.084*	0.201*	0.060*	0.131*	0.074*	0.168*
One	0.101*	0.243*	0.038*	0.080*	0.071*	0.157*
Two (REF)	0.134	0.320	0.032	0.070	0.082	0.188
Three or more	0.122*	0.277*	0.020*	0.042*	0.071*	0.151*
Missing	0.137	0.273*	0.045*	0.104*	0.093	0.187
Metropolitan status						
Lives in metro area (REF)	0.126	0.294	0.040	0.083	0.084	0.183
Lives outside metro area	0.049*	0.165*	0.010*	0.026*	0.030*	0.093*
Unknown	0.135*	0.279	0.043	0.084	0.091*	0.179
State earnings/wages						
Lowest quintile	0.064*	0.183*	0.012*	0.032*	0.039*	0.104*
Middle three quintiles (REF)	0.099	0.255	0.027	0.061	0.064	0.155
Highest quintile	0.151*	0.318*	0.055*	0.103*	0.104*	0.205*
N	34,403	23,645	33,771	26,852	68,174	50,497

Source: Authors' calculations from SIPP matched to DER, SER, and Numident. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants.
Notes: MDC = Country of origin has higher per capita GDP; LDC = country of origin has lower per capita GDP. See endnote 18 for information on state earnings rankings.
"*" indicates prevalence statistically differs from the reference group (denoted by "REF") for this row and column at p<0.05 level.

Table 4. Shares of Individuals Earning over the Taxable Maximum, by Current Job Characteristics: Workers Ages 30 to 67 at a Point in Time (2004, 2009) and All Individuals Ages 45 to 67 over the Last 20 Years

	Shares over taxable maximum					
Characteristic	Men		Women		All	
	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)
Occupation in current year						
Managerial	0.275*	0.526*	0.111*	0.220*	0.204*	0.399*
Professional	0.221*	0.454*	0.051*	0.121*	0.122*	0.258*
Sales	0.153*	0.428*	0.046*	0.144*	0.109*	0.308*
Clerical/administrative /support	0.076*	0.252*	0.011*	0.048*	0.021*	0.078*
Service	0.021	0.099*	0.005	0.027*	0.010*	0.051*
Other (mostly blue collar) (REF)	0.023	0.129	0.004	0.018	0.017	0.095
Occupation missing	0.012*	0.194*	c	0.035*	0.007*	0.096*
Industry in current year						
Agriculture, mining, transport, warehouses, utilities	0.084*	0.209*	0.024	0.068	0.070*	0.175*
Construction	0.050*	0.204*	0.045*	0.121*	0.049*	0.195*
Manufacturing	0.134	0.320	0.071*	0.122	0.115*	0.260*
Wholesale trade	0.131	0.350*	0.067*	0.151*	0.110*	0.285*
Retail trade	0.075	0.225*	0.024	0.057*	0.050*	0.141*
Information	0.199*	0.458*	0.071*	0.169*	0.146*	0.325*
Finance/insurance/real estate	0.245*	0.512*	0.063*	0.169*	0.142*	0.321*
Professional/scientific	0.199*	0.459*	0.063*	0.160*	0.138*	0.326*
Education/health/social service (REF)	0.140	0.294	0.027	0.071	0.054	0.124
Arts/entertainment	0.032*	0.148	0.005	0.034*	0.017	0.087*
Other services	0.030*	0.168*	0.011*	0.041	0.020*	0.101
Public admin/active duty military	0.088*	0.212	0.029*	0.076	0.062	0.147*
Industry missing	0.012*	0.194*	c	0.035*	0.007*	0.096*
Firm size						
Missing	0.010*	0.192*	c	0.036	0.007*	0.096
<25	0.071*	0.293	0.020*	0.087	0.048*	0.202*
25–99	0.115*	0.281	0.024*	0.073*	0.072*	0.180
100 or more (REF)	0.141	0.297	0.045	0.097	0.094	0.196
N	34,403	23,645	33,771	26,852	68,174	50,497

Source: Authors' calculations from SIPP matched to DER, SER, and Numident. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants.
Notes: "*" indicates prevalence statistically differs from the reference group (denoted by "REF") for this row and column at p<0.05 level. "+" indicates combined with row below for this analysis to maintain adequate sample sizes. "c" indicates cell sizes too small to be reliable.
"Other" occupation category is comprised of jobs in production, farm/forestry/fisheries, repair, construction, extraction, and operators.

Table 5. Shares of Individuals Earning over the Taxable Maximum, by Work Experience: Workers Ages 30 to 67 at a Point in Time (2004, 2009) and All Individuals Ages 45 to 67 over the Last 20 Years

	Shares over taxable maximum					
Characteristic	Men		Women		All	
	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)
Usual hours on current job						
<20	0.049*	0.210*	0.009*	0.044	0.027*	0.112*
20–29	0.066	0.251*	0.014*	0.071	0.035*	0.149
30–34	0.077	0.275*	0.027	0.071	0.050	0.162*
35–39	0.068	0.226*	0.023*	0.063	0.040*	0.126
40 (REF)	0.071	0.200	0.029	0.061	0.051	0.133
41–44	0.131*	0.317*	0.059*	0.134*	0.103*	0.243*
45–49	0.185*	0.409*	0.080*	0.161*	0.148*	0.318*
50 or more	0.222*	0.448*	0.115*	0.225*	0.188*	0.372*
Tenure on current job (in years)						
0 or missing	0.027*	0.195	0.006*	0.039*	0.016*	0.101
< 5	0.096*	0.286	0.029*	0.088	0.062*	0.184
5–9 (REF)	0.114	0.286	0.037	0.090	0.076	0.184
10–14	0.131*	0.271	0.038	0.084	0.088*	0.178
15–24	0.155*	0.302	0.056*	0.096*	0.111*	0.205*
25 or more	0.157*	0.337*	0.057*	0.110*	0.119*	0.249*
OASDI–covered work years						
<15	0.066*	0.039*	0.017*	0.007*	0.038*	0.016*
15–19	0.068*	0.079*	0.023*	0.017*	0.045*	0.038*
20–29 (REF)	0.117	0.159	0.038	0.051	0.077	0.090
30–34	0.145*	0.259*	0.049*	0.100*	0.099*	0.179*
35 or more	0.140*	0.369*	0.048*	0.136*	0.106*	0.283*
N	34,403	23,645	33,771	26,852	68,174	50,497

Source: Authors' calculations from SIPP matched to DER, SER, and Numident. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants.
Notes: "*" indicates prevalence statistically differs from the reference group for this row and column (denoted by "REF") at p<0.05 level.

Table 6. Distribution of All Earners over the Taxable Maximum, by Amount Earned over the Maximum and Gender, 2004 and 2009

Amount over maximum/AWI	Men	Women	All
0.01 to 0.049	0.045	0.054	0.047
0.05 to 0.099	0.033	0.056	0.038
0.10 to 0.149	0.039	0.038	0.039
0.15 to 0.199	0.035	0.046	0.038
0.20 to 0.249	0.034	0.040	0.036
0.25 to 0.299	0.030	0.039	0.032
0.30 to 0.349	0.031	0.048	0.035
0.35 to 0.399	0.031	0.032	0.031
0.40 to 0.449	0.029	0.027	0.028
0.45 to 0.499	0.025	0.029	0.026
0.50 to 0.549	0.018	0.014	0.017
0.55 to 0.599	0.026	0.030	0.027
0.60 to 0.649	0.020	0.024	0.021
0.65 to 0.699	0.017	0.013	0.016
0.70 to 0.749	0.015	0.027	0.017
0.75 to 0.799	0.018	0.023	0.019
0.80 to 0.849	0.017	0.019	0.017
0.85 to 0.899	0.016	0.023	0.018
0.90 to 0.949	0.015	0.019	0.016
0.95 to 0.999	0.017	0.017	0.017
1.00 to 1.499	0.121	0.114	0.119
1.50 to 1.999	0.080	0.050	0.074
2.00 to 2.499	0.053	0.042	0.051
2.50 to 2.999	0.036	0.040	0.037
3.00 to 3.499	0.035	0.027	0.033
3.50 to 3.999	0.021	0.025	0.022
4.00 to 4.499	0.019	0.011	0.017
4.50 to 4.999	0.017	0.013	0.016
5.00 to 5.999	0.021	0.016	0.020
6.00 to 6.999	0.016	0.011	0.015
> = 7	0.071	0.034	0.063
N	4,088	1,180	5,268

Source: Authors' calculations from SIPP matched to DER, SER, and Numident. Sample weights account for relative probability of matching to the administrative data. Sample excludes imputed other–than–legal immigrants.

Table 7. Prevalence of Very Low Annual Earnings (Defined as Earnings of Less than One Social Security Covered Quarter) Among Workers, by Age and Sex, 2004 and 2009

	Men	Women	All
0–16	0.303	0.307	0.305
17–19	0.129	0.129	0.129
20–24	0.049	0.059	0.054
25–29	0.022	0.034	0.028
30–34	0.015	0.026	0.021
35–39	0.010	0.031	0.020
40–44	0.012	0.024	0.018
45–49	0.013	0.022	0.017
50–54	0.016	0.024	0.020
55–59	0.027	0.030	0.029
60–64	0.059	0.058	0.058
65–69	0.109	0.082	0.097
70–74	0.141	0.163	0.150
75 plus	0.223	0.261	0.239
All	0.039	0.048	0.044
N	46,050	45,898	91,948

Source: Authors' calculations from SIPP matched to SER and DER. Restricted to workers with OASDI earnings during the year. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants.

Table 8. Distribution of Covered Work Years through Age 60 for 1947 through 1950 Birth Cohorts Using Four Definitions of Work Years: All Individuals and Those at Greatest Risk of Working a Full Covered Career (Non-Immigrants without DI Experience or Significant Uncovered Work)

	Share								
	Men			Women			All		
Number of work years	A: All	B: Non-DI, non-immig.	C: B + no 10+ uncov.	A: All	B: Non-DI, non-immig.	C: B+ no 10+ uncov.	A: All	B: Non-DI, non-immig.	C: B+ no 10+ uncov.
Any earnings									
<10	0.03	0.03	0.02	0.09	0.07	0.06	0.06	0.05	0.04
10–14	0.03	0.02	0.01	0.06	0.05	0.04	0.05	0.04	0.03
15–19	0.04	0.03	0.02	0.07	0.06	0.05	0.06	0.04	0.04
20–24	0.05	0.03	0.02	0.09	0.08	0.08	0.07	0.06	0.05
25–29	0.05	0.04	0.04	0.12	0.11	0.11	0.09	0.08	0.08
30–34	0.08	0.06	0.06	0.13	0.13	0.13	0.10	0.10	0.10
35–39	0.15	0.15	0.15	0.17	0.19	0.19	0.16	0.17	0.17
40 or more	0.56	0.65	0.67	0.27	0.32	0.33	0.41	0.47	0.49
At least four covered quarters									
<10	0.05	0.04	0.02	0.13	0.11	0.09	0.09	0.08	0.06
10–14	0.04	0.03	0.02	0.08	0.07	0.06	0.06	0.05	0.04
15–19	0.05	0.03	0.03	0.09	0.08	0.07	0.07	0.06	0.05
20–24	0.05	0.03	0.03	0.10	0.09	0.09	0.08	0.06	0.06
25–29	0.06	0.04	0.04	0.11	0.11	0.11	0.09	0.08	0.08
30–34	0.09	0.08	0.07	0.13	0.14	0.14	0.11	0.11	0.11
35–39	0.18	0.18	0.19	0.17	0.18	0.19	0.17	0.18	0.19
40 or more	0.48	0.57	0.59	0.20	0.23	0.24	0.33	0.39	0.40
At least half time, half year at minimum wage									
<10	0.06	0.05	0.03	0.15	0.13	0.11	0.10	0.09	0.07
10–14	0.04	0.03	0.03	0.08	0.07	0.06	0.07	0.05	0.05
15–19	0.05	0.03	0.03	0.09	0.08	0.08	0.07	0.06	0.05
20–24	0.05	0.03	0.03	0.10	0.09	0.09	0.08	0.07	0.06
25–29	0.07	0.05	0.05	0.12	0.12	0.12	0.10	0.09	0.09
30–34	0.11	0.09	0.10	0.14	0.14	0.15	0.12	0.12	0.12
35–39	0.22	0.22	0.22	0.18	0.20	0.21	0.20	0.21	0.22
40 or more	0.49	0.49	0.51	0.14	0.16	0.17	0.27	0.32	0.33
At least 15 percent of old law taxable maximum ($15,840 in 2011)									
<10	0.08	0.07	0.05	0.23	0.21	0.18	0.16	0.14	0.12
10–14	0.05	0.04	0.03	0.10	0.09	0.09	0.08	0.06	0.06
15–19	0.05	0.03	0.03	0.08	0.08	0.08	0.07	0.06	0.06
20–24	0.06	0.05	0.05	0.11	0.10	0.10	0.09	0.08	0.08
25–29	0.08	0.07	0.07	0.12	0.12	0.12	0.10	0.09	0.10
30–34	0.12	0.12	0.12	0.13	0.14	0.14	0.13	0.13	0.13
35–39	0.23	0.24	0.25	0.15	0.17	0.18	0.19	0.21	0.21
40 or more	0.32	0.38	0.40	0.09	0.10	0.11	0.20	0.23	0.24
N	3,214	2,625	2,536	3,645	3,028	2,916	6,589	5,653	5,452

Source: Authors' calculations from SIPP matched to SER, DER, and Numident.
Notes: "Non-DI, non-immig." indicates person did not immigrate to U.S. after childhood, has no DI worker experience. "No 10+ uncov." indicates person did not have at least 10 years of uncovered earnings exceeding one quarter. Entries may not sum to one because of rounding.

Table 9a. Distribution of Covered Work Years through Age 60 for 1947 through 1950 Cohorts by "Maximum Earnings" (Two-Year Average), Excludes Adult Immigrants and DI Beneficiaries, By Sex

Sex and work years	Average earnings over two highest career years <1*AWI	1.00–1.49	1.50–1.99	2.00–high
All men				
<20	0.43	0.10	0.10	0.14
20–24	0.12	0.05	0.04	0.02
25–34	0.22	0.24	0.16	0.10
35–39	0.09	0.20	0.18	0.19
40 or more	0.13	0.40	0.53	0.61
Total	1.00	1.00	1.00	1.00
N	576	898	981	1810
Men not on DI, not immigrating as adults, and not long term uncovered				
<20	0.29	0.04	0.05	0.04
20–24	0.10	0.03	0.02	0.01
25–34	0.23	0.22	0.11	0.07
35–39	0.15	0.21	0.19	0.18
40 or more	0.23	0.51	0.62	0.69
Total	1.00	1.00	1.00	1.00
N	327	658	784	1532
All women				
<20	0.46	0.13	0.16	0.12
20–24	0.13	0.09	0.06	0.03
25–34	0.25	0.30	0.19	0.18
35–39	0.10	0.22	0.24	0.28
40 or more	0.06	0.24	0.35	0.39
Total	1.00	1.00	1.00	1.00
N	2,473	1,205	638	552
Women, not immigrating as adults, and not long term uncovered				
<20	0.40	0.10	0.09	0.07
20–24	0.13	0.08	0.05	0.03
25–34	0.29	0.30	0.19	0.17
35–39	0.11	0.24	0.26	0.29
40 or more	0.08	0.29	0.41	0.44
Total	1.00	1.00	1.00	1.00
N	1,877	1,016	533	465

Source: Authors' calculations from SIPP matched to DER, SER, and Numident.
Notes: Entries may not sum to one because of rounding. AWI = Average Wage Index.

Table 9b. Joint Distribution of Covered Work Years and AIME/Poverty at Age 62 for 1945 through 1948 Cohorts, Excludes Adult Immigrants and DI Beneficiaries

	AIME/Poverty			
Sex and work years	**<250% poverty**	**250–399%**	**400% or higher**	**All**
Men				
<25	0.169	0.007	0.002	0.180
> = 25	0.096	0.204	0.521	0.821
All	0.265	0.212	0.533	1.000
N	1,548	1,282	3,585	6,415
	<250% poverty	**250–349%**	**350% or higher**	**All**
Women				
<25	0.404	0.008	0.003	0.415
.> = 25	0.231	0.153	0.202	0.586
All	0.634	0.161	0.204	1.000
N	4,842	1,172	1,448	7,462

Source: Authors’ calculations from SIPP matched to DER, SER, and Numident.
Notes: Entries may not sum to one because of rounding. Poverty level used is census non-aged level.

Table 10a. Distribution of Total Years over the Last 20 Years over the Taxable Maximum for Individuals Ages 30 to 67, by Age and Sex, 2004 and 2008

	Share with this number of earnings years									
		Distribution among those earning over taxable maximum at least once								
	None	1	2	3	4–5	6–7	8–9	10 or more		
								All	10–14	15+
Men										
30–39	0.86	0.25	0.14	0.12	0.18	0.13	0.09	0.08	c	c
40–44	0.80	0.19	0.09	0.07	0.14	0.10	0.09	0.32	0.24	0.08
45–49	0.77	0.13	0.09	0.08	0.10	0.09	0.08	0.41	0.18	0.23
50–59	0.73	0.15	0.07	0.06	0.10	0.08	0.06	0.47	0.17	0.31
60–67	0.69	0.16	0.08	0.06	0.09	0.08	0.08	0.45	0.19	0.25
N				40,384						
Women										
30–39	0.95	0.29	0.16	0.13	0.20	0.12	0.06	0.03	c	c
40–44	0.93	0.25	0.13	0.11	0.11	0.13	0.09	0.18	0.14	0.04
45–49	0.94	0.23	0.11	0.09	0.16	0.10	0.05	0.26	0.15	0.10
50–59	0.92	0.23	0.12	0.08	0.09	0.08	0.08	0.32	0.15	0.16
60–67	0.94	0.29	0.12	0.07	0.09	0.11	0.08	0.22	0.12	0.10
N				45,352						
All										
30–39	0.91	0.26	0.14	0.12	0.19	0.13	0.08	0.07	c	c
40–44	0.86	0.20	0.10	0.08	0.13	0.11	0.09	0.28	0.21	0.07
45–49	0.85	0.16	0.10	0.08	0.12	0.10	0.08	0.37	0.17	0.20
50–59	0.83	0.17	0.08	0.07	0.10	0.08	0.07	0.44	0.16	0.27
60–67	0.82	0.18	0.09	0.07	0.09	0.09	0.08	0.41	0.18	0.23
N				85,736						

Source: Authors' calculations from 2004 and 2008 SIPP matched to SER and DER. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants.
Notes: "c" indicates cell sizes too small to be reliable. Entries may not sum to 100 percent because of rounding.

Table 10b. Distribution of Total Years over the Last 28 Years over the Taxable Maximum for Individuals Ages 30 to 67 in 2010, by Age and Sex

	Share with this number of earnings years										
		Distribution among those earning over taxable maximum at least once									
	None	1	2	3	4–5	6–7	8–9	10 or more			
								All	10–14	15–19	20+
Men											
30–39	0.91	0.29	0.14	0.11	0.19	0.13	0.07	0.07	c	c	c
40–44	0.82	0.19	0.11	0.08	0.13	0.12	0.10	0.27	c	c	c
45–49	0.80	0.17	0.07	0.07	0.13	0.09	0.09	0.39	0.21	0.15	0.03
50–59	0.73	0.17	0.08	0.06	0.09	0.08	0.06	0.47	0.14	0.14	0.20
60–67	0.65	0.17	0.08	0.06	0.08	0.06	0.05	0.49	0.13	0.12	0.24
N					47,278						
Women											
30–39	0.96	0.30	0.16	0.15	0.21	0.10	0.05	0.02	c	c	c
40–44	0.94	0.26	0.11	0.09	0.18	0.13	0.07	0.17	c	c	c
45–49	0.92	0.24	0.12	0.09	0.13	0.13	0.08	0.22	0.13	0.07	0.02
50–59	0.91	0.25	0.09	0.10	0.11	0.08	0.07	0.30	0.13	0.09	0.09
60–67	0.91	0.31	0.12	0.05	0.08	0.08	0.07	0.29	0.12	0.08	0.07
N					52,338						
All											
30–39	0.93	0.29	0.14	0.13	0.20	0.12	0.07	0.05	c	c	c
40–44	0.88	0.21	0.11	0.09	0.14	0.12	0.09	0.24	c	c	c
45–49	0.86	0.19	0.08	0.07	0.13	0.11	0.09	0.34	0.19	0.12	0.03
50–59	0.82	0.19	0.08	0.07	0.09	0.08	0.06	0.43	0.13	0.12	0.17
60–67	0.78	0.20	0.09	0.06	0.08	0.07	0.06	0.45	0.13	0.11	0.21
N					99,616						

Source: Authors’ calculations from 2004 and 2008 SIPP matched to DER, SER, and Numident. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants.
Notes: “c” indicates cell sizes too small to be reliable. Entries may not sum to 100 percent because of rounding.

Table 11. Entries into and Exits from Earnings over the Taxable Maximum at Ages 30 to 67 in 2004 and 2009, by Gender, Education, and History of Earning over the Taxable Maximum

	Not earning over taxable maximum in year one		Earning over taxable maximum in year one	
	Share earning over taxable maximum in year two	Share remaining below taxable maximum in year two	Share continuing to earn over taxable maximum in year two	Share no longer earning over taxable maximum in year two
All	0.01	0.99	0.83	0.17
Gender				
Men	0.02	0.98	0.84	0.16
Women	0.01	0.99	0.80	0.20
History of earning over the taxable maximum				
Earned over cap at least once in last 10 years	0.12	0.88	n/a	n/a
Did not earn over cap in last 10 years	0.01	0.99	n/a	n/a
Current spell is 1 year	n/a	n/a	0.59	0.41
Current spell is 2–3 years	n/a	n/a	0.78	0.22
Current spell is 4–5 years	n/a	n/a	0.84	0.16
Current spell is 6 or more years	n/a	n/a	0.91	0.09
Completed education				
< College degree	0.01	0.99	0.71	0.29
Bachelor's degree	0.03	0.97	0.85	0.15
Master's degree	0.03	0.97	0.86	0.14
Professional degree	0.08	0.92	0.93	0.07
Doctoral degree	0.07	0.93	0.89	0.11
N (all)	56,381		5,160	

Source: Authors' calculations from 2004 and 2008 SIPP matched to DER, SER, and Numident.
Note: Sample only includes workers (defined as earnings over zero) in both periods. Sample weights account for relative probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants.

Table 12. Five-Year Earnings Transition Matrices at Ages 35 to 59 in Ending Period by Earnings Quintile, 1996, 2001, 2004 and 2009 SIPP

Men Using Lower Earnings Bound of Zero in Both Periods and at Least Three Positive Earnings Years over the Past Five

		This year's earnings quintile					
		Bottom	Second	Middle	Fourth	Top	All
	Bottom	65.0	30.7	3.4	0.7	0.2	100.0
Average of	Second	17.9	52.4	26.3	3.1	0.4	100.0
previous	Middle	8.7	11.7	57.2	20.7	1.8	100.0
five years	Fourth	5.2	3.9	11.1	64.9	14.9	100.0
earnings	Top	3.2	1.4	2.0	10.5	82.8	100.0
	N			42,335			

Women Using Lower Earnings Bound of Zero in Current Periods and at Least Three Positive Earnings Years over the Past Five

		This year's earnings quintile					
		Bottom	Second	Middle	Fourth	Top	All
	Bottom	62.0	32.5	4.4	0.9	0.2	100.0
Average of	Second	19.4	50.0	26.4	3.6	0.6	100.0
previous	Middle	9.2	11.9	55.9	21.0	2.0	100.0
five years	Fourth	5.5	4.1	11.2	64.7	14.5	100.0
earnings	Top	3.8	1.5	2.1	9.7	82.8	100.0
	N			40,635			

Source: Authors' calculations from 1996, 2001, 2004, and 2008 SIPP matched to DER, SER, and Numident. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants.
Notes: Entries may not sum to 100 percent because of rounding.

Table 13. Ten-Year Earnings Transition Matrices at Ages 30 to 64 in Ending Period by Earnings Quintile, 1996, 2001, 2004, and 2009 SIPP

Men Using Lower Earnings Bound of Zero in Current Period and at Least Six Positive Earnings Years over the Past Ten

		This year's earnings quintile					
		Bottom	Second	Middle	Fourth	Top	All
	Bottom	53.3	38.5	6.8	1.1	0.3	100.0
Average of	Second	19.7	39.9	32.7	6.9	0.8	100.0
previous	Middle	12.4	13.6	44.9	25.0	4.0	100.0
10 years	Fourth	8.7	5.4	12.8	54.5	18.5	100.0
earnings	Top	5.9	2.5	2.7	12.5	76.3	100.0
	N			58,167			

Women Using Lower Earnings Bound of Zero in Current Period and at Least Six Positive Earnings Years over the Past Ten

		This year's earnings quintile					
		Bottom	Second	Middle	Fourth	Top	All
	Bottom	48.0	41.5	9.0	1.4	0.1	100.0
Average of	Second	23.2	35.6	32.3	7.8	1.1	100.0
previous	Middle	13.6	13.5	43.4	25.7	3.8	100.0
10 years	Fourth	8.9	6.4	12.4	53.4	18.9	100.0
earnings	Top	6.3	2.9	2.8	11.8	76.1	100.0
	N			56,289			

Source: Authors' calculations from 1996, 2001, 2004, and 2008 SIPP matched to DER, SER, and Numident. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants.
Notes: Entries may not sum to 100 percent because of rounding.

Table 14a. Deciles of Worker Benefit Replacement Rate (PIA/AIMEs) for Men under Current Law and Alternative Assumptions about Taxable Maximum: 1941–47 Birth Cohorts as of 2010

	Current law					Remove taxable maximum starting in 1983, pay benefits				Remove taxable maximum starting in 1983, do not pay benefits			
Decile	All	Never earned over cap	Earned over taxable maximum at least once				Earned over taxable maximum at least once				Earned over taxable maximum at least once		
			All	1–9 years	10+ years	All	All	1–9 years	10+ years	All	All	1–9 years	10+ years
Lowest	0.34	0.39	0.32	0.34	0.32	0.30	0.25	0.33	0.22	0.28	0.19	0.33	0.13
2	0.36	0.42	0.33	0.35	0.32	0.34	0.29	0.34	0.25	0.34	0.25	0.34	0.19
3	0.38	0.43	0.34	0.36	0.33	0.38	0.31	0.35	0.27	0.37	0.28	0.35	0.23
4	0.41	0.44	0.34	0.37	0.33	0.41	0.32	0.36	0.29	0.41	0.31	0.36	0.25
5	0.43	0.46	0.35	0.38	0.33	0.43	0.34	0.37	0.30	0.43	0.33	0.37	0.27
6	0.45	0.49	0.36	0.39	0.34	0.45	0.35	0.38	0.31	0.44	0.34	0.38	0.28
7	0.47	0.53	0.37	0.41	0.34	0.47	0.36	0.40	0.32	0.47	0.36	0.39	0.30
8	0.53	0.61	0.40	0.42	0.35	0.53	0.39	0.42	0.32	0.53	0.38	0.41	0.31
9	0.68	0.79	0.42	0.45	0.37	0.68	0.42	0.44	0.34	0.67	0.41	0.44	0.33
Highest	0.90	0.90	0.88	0.88	0.49	0.90	0.75	0.75	0.44	0.90	0.74	0.74	0.40
N	5,909	3,922	1,987	1,016	971								

Source: Authors' calculations from SIPP matched to DER, SER, and Numident. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants and individuals with AIME of zero.
Notes: Does not account for actuarial reductions, which will apply to the majority of beneficiaries, or spouse and survivor benefits. AIME and PIA computed as of age 62.

Table 14b. Deciles of Worker Benefit Replacement Rate (PIA/AIMEs) for Women under Current Law and Alternative Assumptions about Taxable Maximum: 1941–47 Birth Cohorts as of 2010

	Current law					Remove taxable maximum starting in 1983, pay benefits				Remove taxable maximum starting in 1983, do not pay benefits			
Decile	All	Never earned over cap	Earned over taxable maximum at least once				Earned over taxable maximum at least once				Earned over taxable maximum at least once		
			All	1–4 years	5+ years	All	All	1–4 years	5+ years	All	All	1–4 years	5+ years
Lowest	0.43	0.44	0.34	0.36	0.33	0.42	0.30	0.36	0.28	0.42	0.27	0.36	0.23
2	0.46	0.48	0.35	0.38	0.34	0.46	0.34	0.38	0.31	0.46	0.32	0.37	0.27
3	0.49	0.50	0.37	0.40	0.35	0.49	0.35	0.40	0.32	0.49	0.35	0.39	0.30
4	0.52	0.54	0.38	0.42	0.36	0.52	0.37	0.42	0.34	0.52	0.36	0.41	0.32
5	0.57	0.59	0.40	0.43	0.37	0.56	0.38	0.43	0.35	0.56	0.38	0.42	0.33
6	0.63	0.65	0.42	0.44	0.38	0.63	0.41	0.43	0.36	0.63	0.39	0.43	0.35
7	0.72	0.75	0.43	0.45	0.40	0.72	0.43	0.45	0.38	0.72	0.42	0.44	0.36
8	0.87	0.90	0.45	0.47	0.42	0.87	0.55	0.47	0.40	0.87	0.43	0.46	0.38
9	0.90	0.90	0.48	0.52	0.44	0.90	0.47	0.52	0.42	0.90	0.47	0.50	0.40
Highest	0.90	0.90	0.85	0.85	0.56	0.90	0.81	0.75	0.48	0.90	0.80	0.80	0.48
N	5,941	5,479	462	229	233								

Source: Authors' calculations from SIPP matched to DER, SER, and Numident. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants and individuals with AIME of zero.
Notes: Does not account for actuarial reductions, which will apply to the majority of beneficiaries, or spouse and survivor benefits. AIME and PIA computed as of age 62.

Table 15. MINT Projections of the Share Not Once Earning over the Taxable Maximum over the Last 20 Years, by Age and Sex, 2020, 2040, and 2060

	2020		2040		2060	
Age	Men	Women	Men	Women	Men	Women
30–39	0.89	0.96	0.90	0.96	0.91	0.96
40–44	0.82	0.93	0.84	0.93	0.84	0.93
45–49	0.77	0.92	0.81	0.92	0.83	0.93
50–59	0.75	0.90	0.78	0.91	0.79	0.91
60–67	0.74	0.92	0.75	0.90	0.80	0.91
N	42,079	36,276	37,780	39,922	42,695	42,216

Source: Authors' computations from MINT7 (dated July, 2013).
Sample excludes imputed other-than-legal immigrants.

Table 16. Projected Distribution of Total Years over the Last 20 Years over the Taxable Maximum for those Exceeding the Cap at Least Once, by Age and Sex, 2020, 2040, and 2060

	Distribution among those earning over taxable maximum at least once																				
	2020							2040							2060						
	1	2	3	4–5	6–7	8–9	10 or more	1	2	3	4–5	6–7	8–9	10 or more	1	2	3	4–5	6–7	8–9	10 or more
Men																					
30–39	0.31	0.16	0.12	0.20	0.09	0.07	0.05	0.28	0.19	0.13	0.19	0.09	0.07	0.05	0.31	0.16	0.14	0.18	0.09	0.07	0.05
40–44	0.21	0.10	0.08	0.15	0.10	0.11	0.24	0.24	0.13	0.07	0.13	0.11	0.10	0.22	0.24	0.12	0.08	0.13	0.09	0.09	0.24
45–49	0.20	0.07	0.05	0.10	0.10	0.08	0.40	0.21	0.11	0.09	0.09	0.06	0.07	0.37	0.21	0.10	0.08	0.11	0.09	0.08	0.32
50–59	0.16	0.09	0.06	0.10	0.07	0.07	0.44	0.21	0.09	0.06	0.09	0.07	0.06	0.42	0.20	0.10	0.06	0.09	0.06	0.07	0.41
60–67	0.17	0.10	0.06	0.09	0.07	0.07	0.45	0.19	0.09	0.05	0.09	0.08	0.07	0.42	0.20	0.10	0.06	0.09	0.08	0.07	0.40
N				6,616							6,666							7,042			
Women																					
30–39	0.30	0.14	0.15	0.22	0.07	0.07	0.05	0.32	0.18	0.14	0.16	0.10	0.06	0.05	0.33	0.15	0.11	0.20	0.08	0.07	0.06
40–44	0.25	0.14	0.13	0.18	0.07	0.08	0.17	0.24	0.12	0.07	0.18	0.09	0.10	0.19	0.21	0.14	0.10	0.16	0.09	0.09	0.21
45–49	0.19	0.10	0.12	0.15	0.06	0.08	0.28	0.18	0.13	0.08	0.14	0.10	0.07	0.30	0.21	0.15	0.09	0.14	0.08	0.10	0.23
50–59	0.21	0.11	0.10	0.12	0.06	0.09	0.31	0.22	0.10	0.08	0.10	0.10	0.07	0.33	0.21	0.10	0.08	0.09	0.10	0.08	0.34
60–67	0.22	0.12	0.08	0.11	0.12	0.06	0.28	0.22	0.10	0.09	0.13	0.09	0.06	0.34	0.21	0.13	0.08	0.10	0.08	0.08	0.34
N				3,039							2,816							3,117			

Source: Authors' computations from MINT7 (dated July, 2013).
Notes: Entries may not sum to 100 percent because of rounding. Sample excludes imputed other-than-legal immigrants.

Table 17. Projected Five-Year Earnings Quintile Transition Matrices at Ages 35 to 59 by Sex, 2020, 2040, and 2060

Five-year average earnings	This year's earnings														
	2020					2040					2060				
Men															
	Bottom	Second	Middle	Fourth	Top	Bottom	Second	Middle	Fourth	Top	Bottom	Second	Middle	Fourth	Top
Bottom	67.5	25.3	5.1	1.5	0.6	65.2	26.7	5.6	2.1	0.4	64.9	27.5	5.5	1.6	0.5
Second	19.3	51.8	23.3	4.7	1.0	20.0	49.9	24.2	4.9	1.1	19.9	48.8	25.5	4.8	0.9
Middle	8.1	16.5	53.5	19.1	2.7	9.0	16.2	52.2	20.4	2.1	8.9	16.5	51.3	21.0	2.4
Fourth	3.6	4.4	15.0	62.8	14.3	4.0	5.1	15.1	60.3	15.5	4.9	4.7	14.4	59.8	16.2
Top	2.6	1.5	2.9	11.7	81.3	2.7	1.8	2.7	12.1	80.7	2.4	2.0	3.0	12.6	80.0
N			18,989					22,847					24,868		
Women															
	Bottom	Second	Middle	Fourth	Top	Bottom	Second	Middle	Fourth	Top	Bottom	Second	Middle	Fourth	Top
Bottom	61.5	29.7	6.2	1.8	0.8	61.1	29.8	6.2	2.3	0.6	61.7	29.3	6.3	2.1	0.7
Second	20.3	47.6	24.8	6.2	1.1	21.3	48.4	23.8	5.4	1.1	19.9	49.2	23.8	6.0	1.1
Middle	9.9	15.2	52.0	19.3	3.5	9.8	14.7	53.6	19.1	2.9	10.2	14.9	52.7	19.5	2.8
Fourth	5.3	4.7	14.1	60.8	15.2	5.6	5.0	13.7	60.9	14.9	5.8	4.5	14.5	60.3	15.0
Top	3.8	2.4	2.7	11.8	79.3	3.1	1.8	2.6	12.2	80.3	3.2	1.8	2.6	12.0	80.4
N			18,648					20,440					22,411		

Source: Authors' computations from MINT7 (dated July, 2013).
Notes: To be included in the sample, individuals need to have worked at least three of the past five years. Sample excludes imputed other-than-legal immigrants. Entries may not sum to 100 percent because of rounding.

Table 18. Projected Ten-Year Earnings Quintile Transition Matrices at Ages 35 to 59 by Sex, 2020, 2040, and 2060

Five-year average earnings	This year's earnings														
	2020					2040					2060				
Men															
	Bottom	Second	Middle	Fourth	Top	Bottom	Second	Middle	Fourth	Top	Bottom	Second	Middle	Fourth	Top
Bottom	58.3	31.7	7.5	1.9	0.7	57.7	32.5	7.1	2.1	0.5	56.4	32.8	8.1	2.1	0.6
Second	22.2	40.2	29.3	7.1	1.3	22.0	41.0	28.1	7.8	1.1	22.5	39.3	29.0	7.9	1.3
Middle	11.3	18.8	42.2	23.6	4.1	11.4	16.9	43.7	24.1	3.9	12.3	17.9	41.7	24.1	4.0
Fourth	6.4	6.6	17.2	52.0	17.8	6.2	6.6	17.1	51.4	18.8	6.5	6.6	17.3	50.7	18.9
Top	3.5	2.0	3.5	15.2	75.9	3.8	2.5	3.8	14.4	75.6	3.7	2.8	3.5	15.1	75.0
N			26,749					30,606					34,109		
Women															
	Bottom	Second	Middle	Fourth	Top	Bottom	Second	Middle	Fourth	Top	Bottom	Second	Middle	Fourth	Top
Bottom	48.6	38.9	9.3	2.4	0.8	50.5	37.3	9.1	2.4	0.8	49.9	38.1	9.2	2.3	0.5
Second	23.5	36.4	30.2	7.9	2.1	22.9	38.6	29.2	8.0	1.3	23.1	38.0	29.5	7.9	1.6
Middle	14.2	14.9	41.8	24.9	4.4	13.8	15.0	43.0	24.2	4.0	13.6	14.3	42.4	25.6	4.0
Fourth	9.4	6.0	14.3	51.3	19.0	8.9	5.8	14.9	51.0	19.4	9.0	6.2	14.8	50.9	19.2
Top	5.4	3.3	4.2	13.5	73.7	5.1	2.9	3.6	14.2	74.4	5.5	2.9	3.9	13.2	74.5
N			25,979					27,398					30,338		

Source: Authors' computations from MINT7 (dated July, 2013).
Notes: To be included in the sample, individuals need to have worked at least six of the past 10 years. Sample excludes imputed other-than-legal immigrants. Entries may not sum to 100 percent because of rounding.

Appendix 1. Earnings in Dynamic Microsimulation Models

The Congressional Budget Office developed the Congressional Budget Office Long-Term dynamic microsimulation (CBOLT) model (2006) for estimating costs and distributional effects of Social Security changes (for example, Congressional Budget Office 2010; 2012). CBOLT uses an age-centered regression technique described by Sabelhaus and Walker (2009) as the foundation for its earnings projections (see also Schwabish and Topoleski 2013). This approach assumes that the effects of most key characteristics vary by age. Age-centered regression also uses data from neighboring ages to smooth across equations. Relying on insights from Carroll, Hall, and Zeldes (1992), the model error structure and bootstrapping techniques serve to preserve the distribution of earnings over time.

MINT7 is the Social Security Administration's SIPP-based work horse model for distributional analysis.[41] SSA developed the model with assistance from researchers from the Urban Institute, Brookings Institution, and RAND. To project its earnings trajectories, MINT7 relies on three distinct sets of algorithms that include both parametric and non-parametric methods (Smith et al. 2010). Table A1.2 provides additional details about how this process works. Through age 55, earnings, along with disability and mortality, are "spliced" in five-year segments, a method that developers chose to ensure internal consistency in these three outcomes. From age 55 onward, MINT uses a regression-based, education-specific trajectory method for the non-retired (i.e., those without a sustained drop in earnings) and a regression method closely tied to beneficiary status for workers who have retired. (MINT defines retirement based on a significant drop in usual hours worked.)[42] Over the projection horizon, about one tenth of one percent of outlier earnings are adjusted. This corresponds to earnings over $720,000 annually at present.

The Urban Institute's Dynamic Simulation of Income Model (DYNASIM), another model based on the SIPP, uses regression models to project earnings. The model employs separate equations for participation, hours, and the natural log of wages. These equations all include complex error structures, with permanent and transitory components. To capture the very highest earners, the model uses a separate process for approximately one-tenth of one percent of male earners who earn more than 200 times the average wage index (over $8 million today).

Table A1.1. Specification of Employment and Earnings Processes in Selected U.S. Microsimulation Models

	CBOLT	DYNASIM	MINT
Regression or match/splice?	Regression	Regression	Combination: splice through age 54, regression thereafter for non-disabled
Key stratifying dimensions?	Single year of age and gender	Gender, race, broad age group	OASI/DI beneficiary status, age, gender, education
Employment	Unemployment spell durations explicitly modeled	Just employed, nonemployed	Just employed, nonemployed
Hours (FT/PT)	Hours and FT/PT	Hours	None (implicit only)
Wage/earnings		Log wage is used along with hours to derive earnings; separate process for high earners	
Alignment?		Yes to AWI and for very high earners	Yes, but only for very high earners
Wage growth?	CBO's longer term projections	Board of Trustees (2012)	Board of Trustees (2012)
Error structures	Bootstrapping	AR-1	

Sources: Congressional Budget Office (2006); Schwabish and Topoleski (2013); Smith et al. (2010).

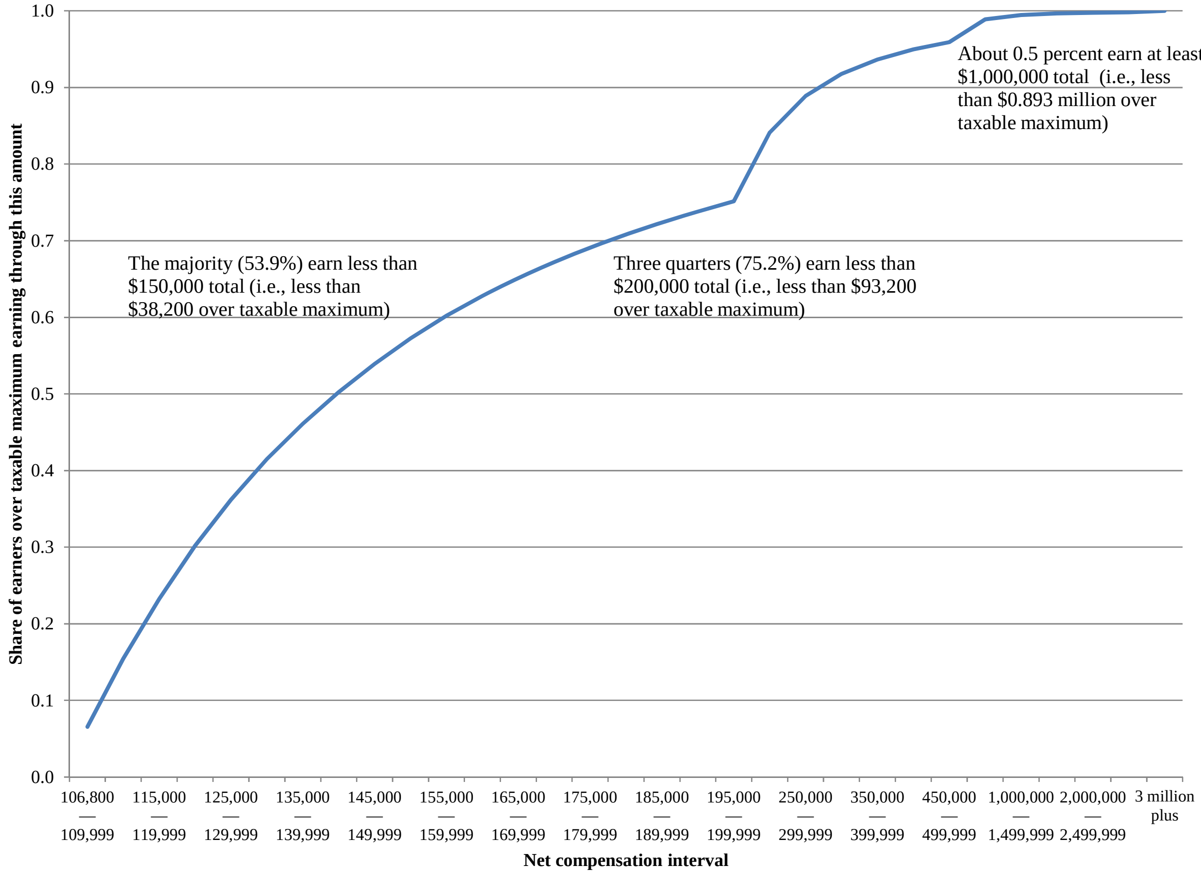
Table A1.2. Details on the Specification of Employment/Earnings in MINT7

Year and age range	Specification	Key explanatory/matching variables	Estimation data source
1951–2010, All ages	Observed from matched earnings records	N/A	N/A
2011+, Ages 16–54 and all workers ever receiving DI benefits	Five year segments of joint earnings/mortality/ DI participation trajectories are "spliced" using a statistical matching algorithm (minimum distance)	SIPP panel, age, gender, death indicator, disability indicator, SSI receipt, report making DC contribution on SIPP, mean monthly earnings group (7 categories), nativity, immigration age and source region if foreign born, earnings status, education, race/ethnicity, class of worker (private or nonprofit, government, other, nonworker)	SIPP matched data
2011+, Ages 55–69 non-disabled, decision to "retire"	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	HRS matched data
2011+, Ages 55–69, non-disabled, "nonretired"	Age-earnings profiles, separately by gender and education, with fixed effects	Age, cohort for women; 0.3 percent of observations are capped due to high earnings (with different caps by education group)	SIPP matched data
2011+, Ages 55–first aged OASI claiming,"retired"	Separate entry and exit models	Age, education, gender, lifetime earnings, work limitations, ethnicity/race, wealth (housing and financial)	HRS matched data
2011+, Ages 60–69, Social Security claimants	Four separate regression for participation (separate entry and exit models for claiming age and subsequent ages) and five separate regression models for earnings for similar groups	Age, education, gender, health status, marital status, lagged employment/ employment duration, lifetime earnings, recent earnings, pension indicators, Social Security incentives (non-contributory, dual entitlement)	SIPP matched data
2011+, Ages 70 and older	Employment modeled using separate equations based on work status last period	Age, education, gender, health status, wealth, lagged employment/ employment duration, recent earnings, lifetime earnings	SIPP matched data

Sources: Smith et al. (2010), Smith and Favreault (2013), unpublished MINT7 documentation.
Notes: SIPP matched data refers to SIPP matched to SER, DER, MBR, and Numident.

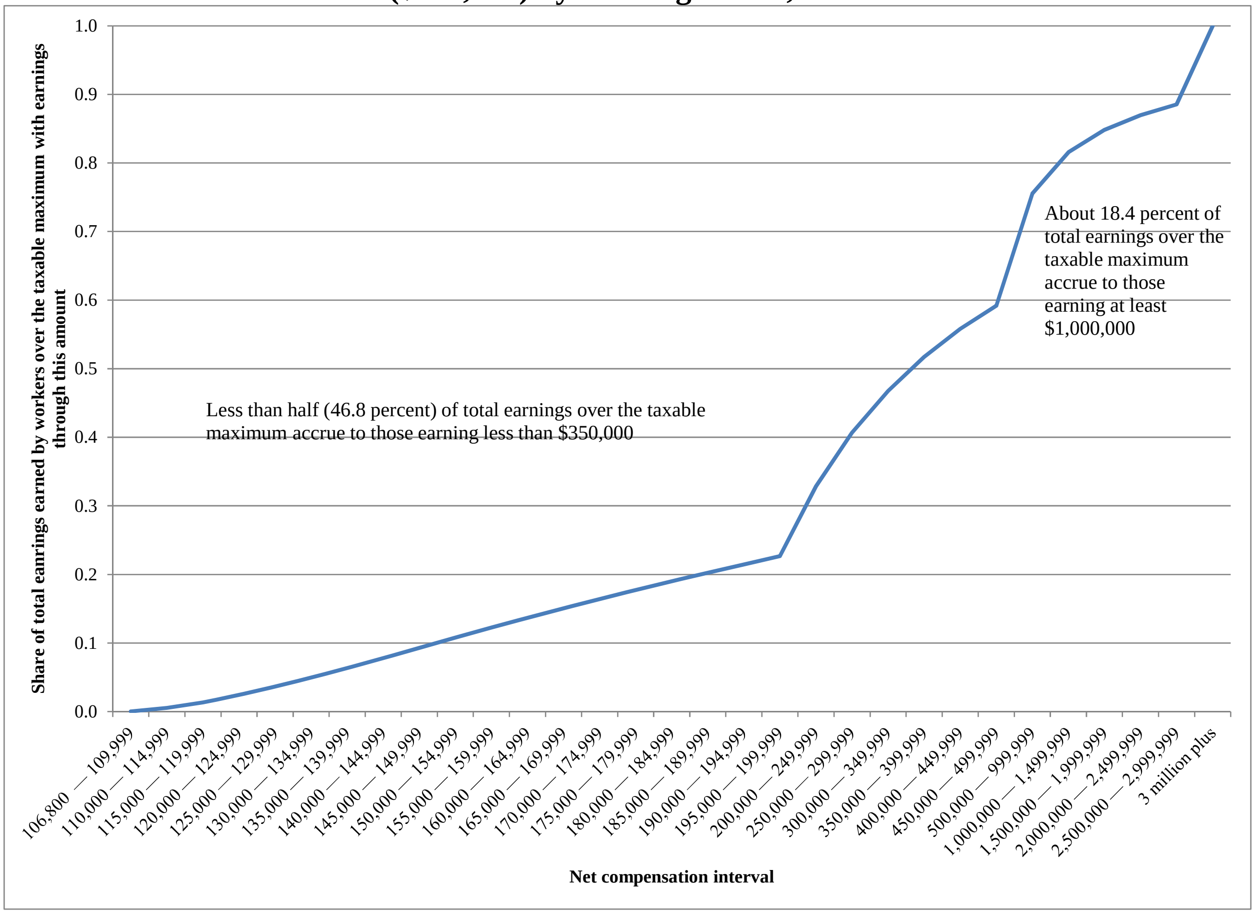
APPENDIX 2. SUPPLEMENTAL TABLES AND FIGURES

Figure A2.1. Cumulative Distribution of Earners with Earnings over the Taxable Maximum ($106,800), 2011



Source: Authors' calculations using administrative data from SSA website (http://www.ssa.gov/cgi-bin/netcomp.cgi?year=2011).
Notes: Assumes that individuals are uniformly distributed in the interval $105,000–109,999. Discontinuities arise when interval sizes change.

Figure A2.2. Cumulative Distribution of Total Earnings over the Taxable Maximum ($106,800) by Earnings Level, 2011



Source: Authors' calculations using administrative data from SSA website (http://www.ssa.gov/cgi-bin/netcomp.cgi?year=2011).
Notes: Assumes that individuals are uniformly distributed in the interval $105,000–109,999.

Table A2.1. Ratio of Earnings Taxable by Social Security to Earnings Taxable by Medicare, 2009, and Share of State and Local Workers in Covered Employment, 2007

State	Ratio of earnings taxable by OASDI to earnings taxable by HI (2009)			State and local covered share (2007)
	All	Men	Women	
All areas	0.822	0.781	0.889	0.936*
Alabama	0.905	0.869	0.963	0.926
Alaska	0.784	0.783	0.786	0.655
Arizona	0.891	0.847	0.961	0.914
Arkansas	0.906	0.871	0.960	0.898
California	0.749	0.713	0.809	0.438
Colorado	0.769	0.745	0.812	0.304
Connecticut	0.685	0.611	0.837	0.716
Delaware	0.881	0.841	0.939	0.944
District of Columbia	0.749	0.701	0.809	0.777
Florida	0.865	0.809	0.951	0.888
Georgia	0.839	0.799	0.902	0.742
Hawaii	0.887	0.847	0.947	0.703
Idaho	0.924	0.895	0.974	0.944
Illinois	0.772	0.737	0.831	0.547
Indiana	0.908	0.876	0.963	0.901
Iowa	0.926	0.894	0.975	0.906
Kansas	0.895	0.860	0.953	0.922
Kentucky	0.884	0.875	0.899	0.747
Louisiana	0.795	0.808	0.773	0.281
Maine	0.843	0.834	0.857	0.542
Maryland	0.831	0.781	0.899	0.907
Massachusetts	0.737	0.698	0.801	0.043
Michigan	0.879	0.831	0.955	0.886
Minnesota	0.879	0.834	0.950	0.939
Mississippi	0.925	0.896	0.969	0.921
Missouri	0.860	0.839	0.892	0.737
Montana	0.922	0.898	0.960	0.873
Nebraska	0.894	0.860	0.948	0.936
Nevada	0.757	0.735	0.795	0.185
New Hampshire	0.867	0.822	0.946	0.883
New Jersey	0.783	0.709	0.911	0.929

Table A2.1. (Continued)

State	Ratio of earnings taxable by OASDI to earnings taxable by HI (2009) All	Men	Women	State and local covered share (2007)
New Mexico	0.890	0.842	0.967	0.899
New York	0.767	0.697	0.878	0.970
North Carolina	0.891	0.850	0.954	0.925
North Dakota	0.906	0.880	0.956	0.872
Ohio	0.774	0.760	0.796	0.026
Oklahoma	0.902	0.864	0.965	0.908
Oregon	0.907	0.875	0.957	0.922
Pennsylvania	0.860	0.812	0.941	0.927
Rhode Island	0.850	0.818	0.898	0.848
South Carolina	0.899	0.858	0.963	0.939
South Dakota	0.901	0.852	0.970	0.932
Tennessee	0.845	0.785	0.944	0.910
Texas	0.798	0.781	0.830	0.477
Utah	0.855	0.807	0.967	0.914
Vermont	0.921	0.885	0.972	0.977
Virginia	0.843	0.797	0.918	0.947
Washington	0.875	0.837	0.939	0.887
West Virginia	0.883	0.848	0.947	0.932
Wisconsin	0.898	0.856	0.965	0.887
Wyoming	0.780	0.706	0.966	0.882
Puerto Rico	0.900	0.898	0.902	0.864
Other	0.937	0.927	0.958	0.203

Source for Medicare and Social Security earnings by state: U.S. Social Security Administration (2012, tables 1 and 4)
Source for state and local covered share: United States Senate (2010, tables 1 and 2, pages 12–13).
* Overall covered share estimate is for 2008, while state-by-state estimates are for 2007.

Table A2.2. Shares of Individuals Earning over 4.5 Times the Average Wage Index, by Demographic Characteristics: Workers Ages 30 to 67 at a Point in Time (2004, 2009) and All Individuals Ages 45 to 67 over the Last 20 Years

	Shares over 4.5*AWI					
Characteristic	Men		Women		All	
	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)
All	0.035	0.097	0.008	0.017	0.022	0.055
Age						
30–34	0.014*	n/a	0.004*	n/a	0.010*	n/a
35–39	0.033*	n/a	0.008	n/a	0.021*	n/a
40–44	0.038	n/a	0.008	n/a	0.024	n/a
45–49 (REF)	0.041	0.085	0.011	0.018	0.026	0.051
50–54	0.039	0.092	0.009	0.018	0.024	0.054
55–59	0.042	0.104*	0.008	0.018	0.025	0.059*
60–67	0.034*	0.107*	0.005*	0.014	0.020*	0.058*
Education						
High school graduate or less	+	0.021*	+	0.003*	+	0.011*
Some college	0.007*	0.046*	0.001*	0.009*	0.004*	0.026*
College graduate (REF)	0.055	0.182	0.013	0.032	0.035	0.107
Master’s degree	0.087*	0.239*	0.017	0.042	0.051*	0.136*
Professional degree	0.315*	0.570*	0.138*	0.228*	0.252*	0.455*
Doctoral degree	0.166*	0.342*	0.067*	0.146*	0.131*	0.276*
Race/ethnicity						
White (REF)	0.042	0.113	0.009	0.019	0.026	0.065
Non-Hispanic Black, Native American, or Hispanic	0.009*	0.029*	0.003*	0.008*	0.006*	0.017*
Asian/Pacific Islander	0.051*	0.122	0.021*	0.031*	0.037*	0.074*
N	34,403	23,645	33,771	26,852	68,174	50,497

Source: Authors’ calculations from SIPP matched to DER, SER, and Numident. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants.
Notes: “*” indicates prevalence statistically differs from the reference group (denoted by “REF”) for the row and column at p<0.05 level.
“+” indicates this row is combined with the row below for this analysis to maintain adequate sample sizes.

Table A2.3. Shares of Individuals Earning over 4.5 Times the Average Wage Index, by Nativity and Family Demographic Characteristics: Workers Ages 30 to 67 at a Point in Time (2004, 2009) and All Individuals Ages 45 to 67 over the Last 20 Years

Characteristic	Shares over 4.5*AWI					
	Men		Women		All	
	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)
Nativity						
Native-born (REF)	0.035	0.098	0.008	0.017	0.022	0.056
Foreign born						
MDC	0.071*	0.158*	0.020*	0.033*	0.046*	0.091*
LDC	0.022*	0.056*	0.007	0.014	0.015*	0.034*
Marital status						
Married (REF)	0.043	0.116	0.009	0.017	0.027	0.067
Widowed/divorced/ separated	0.013*	0.049*	0.005*	0.014	0.008*	0.027*
Never married	0.015*	0.036*	0.008	0.028*	0.011*	0.032*
Number of children ever born						
None	0.019*	0.059*	0.012*	0.034*	0.016*	0.047*
One	0.024*	0.084*	0.008	0.017	0.016*	0.048*
Two (REF)	0.043	0.119	0.007	0.016	0.025	0.064
Three or more	0.044	0.103*	0.006	0.009*	0.025	0.053*
Missing	0.048	0.108	0.010	0.028*	0.030	0.067
Metropolitan status						
Lives in metro area (REF)	0.038	0.107	0.009	0.020	0.024	0.061
Lives outside metro area or unknown	0.019*	0.059*	0.003*	0.007*	0.011*	0.055*
State earnings/wages						
Lowest quintile	0.019*	0.056*	0.003	0.009	0.011*	0.031*
Middle three quintiles (REF)	0.030	0.091	0.006	0.014	0.018	0.051
Highest quintile	0.046*	0.116*	0.013*	0.025*	0.030*	0.068*
N	34,403	23,645	33,771	26,852	68,174	50,497

Source: Authors' calculations from SIPP matched to DER, SER, and Numident. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants.
Notes: "*" indicates prevalence statistically differs from the reference group (denoted by "REF") for the row and column at p<0.05 level. See endnote 18 for information on state earnings rankings.

Table A2.4. Shares over 4.5 Times the Average Wage Index, by Current Job Characteristics: Workers Ages 30 to 67 at a Point in Time (2004, 2009) and All Individuals Ages 45 to 67 over the Last 20 Years

Characteristic	Shares over 4.5*AWI					
	Men		Women		All	
	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)
Occupation in current year						
Managerial	0.095*	0.247*	0.025*	0.057*	0.065*	0.168*
Professional	0.066*	0.189*	0.012*	0.028*	0.035*	0.094*
Sales	0.051*	0.176*	0.009*	0.027*	0.034*	0.113*
Clerical/administrative	+	0.087*	+	0.011*	+	0.022
Service/other (REF)	0.004	0.018	0.001	0.003	0.003	0.013
Missing	c	0.054*	c	0.010*	c	0.026*
Industry in current year						
Agriculture/forest/ fishery/mining/utility/ construction/transporta-tion/warehouse	0.015*	0.060*	0.008	0.017	0.014	0.052*
Manufacturing	0.029	0.096	0.016	0.032	0.025	0.077
Wholesale or retail trade	0.026	0.092*	0.005	0.013	0.017*	0.056*
Information	0.060*	0.129	0.018*	0.045*	0.042*	0.090*
Finance/insurance/real	0.098*	0.252*	0.017*	0.035*	0.052*	0.131*
Professional/scientific/ mangement/admin service	0.064*	0.219*	0.019*	0.049*	0.044*	0.144*
Other (see notes) (REF)	0.032	0.086	0.004	0.013	0.014	0.038
Missing	c	0.054*	c	0.010*	c	0.026*
Firm size						
<25	0.030*	0.129*	0.006*	0.025*	0.020*	0.083*
25–99	0.038	0.122*	0.005*	0.016	0.023	0.071*
100 or more (REF)	0.039	0.100	0.010	0.020	0.025	0.059
Missing	c	0.053	c	0.010*	c	0.027*
N	34,403	23,645	33,771	26,852	68,174	50,497

Source: Authors' calculations from SIPP matched to DER, SER, and Numident. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants.
Notes: "*" indicates prevalence statistically differs from the reference group (denoted by "REF") for the row and column at p<0.05 level,"+" indicates this row is combined with the row below for this analysis to maintain adequate sample sizes, "c" indicates cell sizes too small to be reliable. "Other" occupation category is comprised of jobs in production, farm/forestry/fisheries, repair, construction, extraction, and operators. "Other" industry category is comprised of jobs in education, health, social services, arts, entertainment, other services, public administration and active duty military.

Table A2.5. Shares over 4.5 Times the Average Wage Index, by Work Experience: Workers Ages 30 to 67 at a Point in Time (2004, 2009) and All Individuals Ages 45 to 67 over the Last 20 Years

Characteristic	Shares over 4.5*AWI					
	Men		Women		All	
	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)	Current (Ages 30–67)	Past 20 (Ages 45–67)
Usual hours on current job						
<20	0.020*	0.068*	0.002	0.011*	0.010	0.034*
20–29	0.020*	0.088*	0.003	0.015*	0.010	0.047*
30–34	0.023*	0.099*	0.011*	0.016*	0.016*	0.055*
35–39	0.021*	0.079*	0.006*	0.014*	0.012*	0.039*
40 (REF)	0.013	0.049	0.003	0.008	0.008	0.029
41–49	0.036*	0.124*	0.012*	0.030*	0.027*	0.087*
50 or more	0.085*	0.214*	0.035*	0.069*	0.069*	0.165*
Tenure on current job						
< 5 (including 0)	0.024*	0.080	0.005*	0.015	0.014*	0.043
5–9 (REF)	0.033	0.111	0.009	0.021	0.021	0.063
10–14	0.044*	0.102	0.010	0.018	0.028*	0.060
15–24	0.048*	0.112	0.013*	0.021	0.032*	0.069
25 or more	0.048*	0.115	0.010	0.020	0.034*	0.078*
OASDI–covered work years						
<15	0.023*	0.037*	0.003*	0.005	0.012*	0.014*
15–19	0.019*	0.044	0.005*	0.007	0.012*	0.019*
20–29 (REF)	0.033	0.062	0.009	0.012	0.021	0.030
30–34	0.045*	0.096*	0.013*	0.026*	0.030*	0.060*
35 or more	0.044*	0.123*	0.009	0.027*	0.031*	0.087*
N	34,403	23,645	33,771	26,852	68,174	50,497

Source: Authors' calculations from SIPP matched to DER, SER, and Numident. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants.
Notes: "*" indicates prevalence statistically differs from the reference group (denoted by "REF") for the row and column at p<0.05 level,"+" indicates combined with the row below for this analysis to maintain adequate sample sizes.

Table A2.6: Logistic Regression Models for Whether Workers' Earnings are Greater than Given Thresholds (the Taxable Maximum or 4.5 Times the Average Wage Index) at Ages 30 to 67, Pooled 2004 and 2008 SIPP Panels

	Earnings over taxable maximum						Earnings over 4.5 times Average Wage Index					
	Just demographic characteristics			Include job characteristics			Just demographic characteristics			Include job characteristics		
	coefficient		SE	coefficient		SE	coefficient		SE	coefficient		SE
Intercept	-9.089	***	0.423	-10.454	***	0.465	-12.325	***	0.795	-14.977	***	0.859
Demographic characteristics												
Age	0.261	***	0.018	0.153	***	0.020	0.307	***	0.034	0.224	***	0.035
Age squared	-0.003	***	0.000	-0.002	***	0.000	-0.003	***	0.000	-0.003	***	0.000
Foreign born indicator (ref = native born)	0.189	*	0.076	0.881	***	0.088	0.281	*	0.118	0.762	***	0.134
Foreign born indicator * country of origin is less developed	-0.302	**	0.097	-0.286	**	0.104	-0.444	**	0.159	-0.431	**	0.165
Female indicator (ref = male)	-0.932	***	0.088	-0.851	***	0.094	-0.836	***	0.179	-0.646	***	0.184
Indicator education < high school (ref = high school graduate)	-1.320	***	0.185	-0.672	***	0.190	-0.917	*	0.364	-0.107		0.370
Indicator education college graduate	1.812	***	0.042	1.291	***	0.047	1.960	***	0.090	1.277	***	0.095
Indicator education more than college graduate	2.544	***	0.043	2.054	***	0.051	3.001	***	0.086	2.330	***	0.095
Unmarried indicator	-0.632	***	0.060	-0.534	***	0.064	-0.667	***	0.116	-0.545	***	0.120
Unmarried female indicator	0.593	***	0.094	0.407	***	0.099	0.520	**	0.190	0.302		0.195
Indicator has one or two children (ref = no children)	0.286	***	0.057	0.261	***	0.062	0.554	***	0.110	0.507	***	0.114
Indicator has three or more children	0.482	***	0.063	0.501	***	0.069	0.942	***	0.117	0.914	***	0.122
Indicator data on number of children is missing	0.669	***	0.111	0.510	***	0.121	1.199	***	0.178	0.992	***	0.187
Female * indicator has one or two children (ref = no children)	-0.612	***	0.096	-0.420	***	0.102	-0.803	***	0.196	-0.619	**	0.201
Female * indicator has three or more children	-1.000	***	0.118	-0.640	***	0.126	-0.984	***	0.225	-0.642	**	0.231
Female * indicator data on number of children is missing	-0.573	**	0.202	-0.374		0.215	-0.934	*	0.377	-0.800	*	0.388
Indicator race is black (ref = non-black)	-0.877	***	0.085	-0.839	***	0.089	-1.040	***	0.181	-0.885	***	0.185
Indicator ethnicity is Hispanic (ref = non-Hispanic)	-0.629	***	0.103	-0.575	***	0.108	-0.936	***	0.228	-0.848	***	0.236
Job characteristics												
Best estimate of annual hours	--			0.030	***	0.001	--			0.030	***	0.002
Total years in the OASDI-covered labor force	--			0.079	***	0.004	--			0.045	***	0.006
Tenure on current job (in years)				0.031	***	0.002	--			0.027	***	0.003
Indicator tenure is missing				-1.065	***	0.290	--			-0.381		0.434
Indicator current occupation is managerial (ref = production or repair in taxable maximum regression, production, repair, operator, forest/farm/fish in higher earner regression)	--			1.703	***	0.072	--			2.580	***	0.205
Indicator current occupation is professional	--			1.146	***	0.073	--			1.982	***	0.207
Indicator current occupation is sales	--			1.328	***	0.082	--			2.290	***	0.216
Indicator current occupation is clerical	--			0.387	***	0.111	--			1.402	***	0.266
Indicator current occupation is service	--			-0.481	**	0.180	--			0.545		0.408
Indicator current occupation is operator	--			-0.713	*	0.288	--			--		
Indicator current occupation is farm/forest/fisheries	--			-0.203		0.306	--			--		
Indicator current occupation is construction	--			0.452	**	0.151	--			1.398	***	0.342
Indicator current industry is finance (ref = all others)	--			0.607	***	0.061	--			0.796	***	0.093
Indicator current industry is professional/scientific	--			0.655	***	0.049	--			0.573	***	0.079
Indicator current industry is information	--			0.597	***	0.089	--			0.732	***	0.145
Indicator individual lives in a metropolitan area	--			0.696	***	0.064	--			0.831	***	0.128
Indicator metropolitan status is missing	--			0.587	***	0.097	--			0.796	***	0.174
Indicator individual lives in state in highest wage/earnings quintile	--			0.511	***	0.037	--			0.257	***	0.063
Indicator individual lives in state in lowest wage/earnings quintile	--			-0.357	***	0.079	--			-0.255		0.136
Indicator firm size is small (<25 employees) (ref = 100+ employees)	--			-0.807	***	0.050	--			-0.228	**	0.077
Indicator firm size is medium (25-99 employees)	--			-0.247	***	0.059	--			0.015		0.097
Indicator firm size is missing	--			-1.800	***	0.540	--			-0.905		0.742
-2 * log likelihood	26,601.54			22,778.26			10,262.78			9,126.87		
Share earning over threshold	0.081			0.081			0.023			0.023		
N	60,896			60,896			60,896			60,896		

*** indicates p<.001; ** indicates p<.01;* indicates p<.05.

Source: Authors' calculations from SIPP matched to DER, SER, and Numident.

Notes: Sample is restricted to individuals who report an average of at least 5 hours per week of work. Endnote 18 has information on state earnings rankings.

Table A2.7: Ordinary Least Squares Regression Models for Natural Logarithm of Amount Earned Over Given Thresholds (Taxable Maximum or 4.5 Times the Average Wage Index) for Workers Ages 30 to 67 Earning over These Thresholds, Pooled 2004 and 2008 SIPP Panels

	Earnings over taxable maximum						Earnings over 4.5 times Average Wage Index					
	Just demographic characteristics			Include job characteristics			Just demographic characteristics			Include job characteristics		
	coefficient		SE	coefficient		SE	coefficient		SE	coefficient		SE
Intercept	7.081	***	0.559	5.636	***	0.567	-1.738		1.143	-2.469	*	1.181
Demographic characteristics												
Age	0.107	***	0.024	0.121	***	0.024	0.081		0.048	0.073		0.049
Age squared	-0.001	***	0.000	-0.001	***	0.000	-0.001		0.001	-0.001		0.001
Foreign born indicator (ref = native born)	0.085		0.092	0.028		0.103	0.059		0.160	0.265		0.185
Foreign born indicator * country of origin is less developed	-0.080		0.119	-0.018		0.117	-0.392		0.219	-0.477	*	0.220
Female indicator (ref = male)	-0.163		0.119	-0.172		0.117	-0.404		0.275	-0.188		0.249
Indicator education < high school (ref = high school graduate)	0.294		0.262	0.394		0.260	--			--		
Indicator education college graduate	0.406	***	0.057	0.312	***	0.059	0.264	*	0.129	0.214		0.131
Indicator education more than college graduate	0.832	***	0.057	0.784	***	0.061	0.449	***	0.120	0.440	***	0.133
Unmarried indicator	-0.100		0.080	-0.109		0.079	0.048		0.174	0.099		0.172
Unmarried female indicator	0.129		0.129	0.101		0.126	-0.373		0.289	-0.503		0.285
Indicator has one or two children (ref = no children)	0.179	*	0.075	0.157	*	0.074	-0.211		0.170	-0.152		0.164
Indicator has three or more children	0.386	***	0.082	0.382	***	0.080	-0.011		0.176	0.036		0.170
Indicator data on number of children is missing	0.477	***	0.134	0.422	**	0.132	0.248		0.250	0.411		0.223
Female * indicator has one or two children (ref = no children)	-0.168		0.130	-0.151		0.128	0.259		0.298	0.059		0.277
Female * indicator has three or more children	-0.275		0.162	-0.254		0.160	0.463		0.335	0.309		0.315
Female * indicator data on number of children is missing	-0.327		0.263	-0.345		0.258	0.810		0.550	--		
Indicator race is black	-0.458	***	0.118	-0.353	**	0.116	-0.189		0.259	-0.215		0.259
Indicator ethnicity is Hispanic (ref = non-Hispanic)	-0.433	***	0.140	-0.414	**	0.138	-0.079		0.324	-0.049		0.323
Job characteristics												
Best estimate of annual hours	--			0.007	***	0.001	--			0.004		0.002
Total years in the OASDI-covered labor force	--			-0.005		0.005	--			0.017	*	0.009
Tenure on current jobs (in years)	--			0.006	*	0.002	--			0.013	**	0.005
Indicator tenure is missing				0.237		0.378	--			0.509		0.408
Indicator current occupation is managerial (ref = production or repair in taxable maximum regression, production, repair, operator, forest/farm/fish, construction in higher earner regression)	--			0.731	***	0.092	--			0.268		0.215
Indicator current occupation is professional	--			0.493	***	0.093	--			0.305		0.222
Indicator current occupation is sales	--			0.807	***	0.104	--			0.180		0.236
Indicator current occupation is clerical	--			0.492	***	0.146	--			0.249		0.323
Indicator current occupation is service	--			0.427		0.243	--			--		
Indicator current occupation is construction	--			0.602	**	0.203	--			--		
Indicator current industry is finance (ref = all others)	--			0.325	***	0.068	--			0.338	**	0.124
Indicator current industry is professional/scientific				0.138	*	0.054				-0.044		0.101
Indicator current industry is information				0.184		0.101				0.083		0.196
Indicator individual lives in a metropolitan area	--			0.143		0.081	--			0.183		0.176
Indicator metropolitan status is missing	--			0.046		0.116	--			0.240		0.237
Indicator individual lives in state in highest wage/earnings quintile	--			0.045		0.043	--			0.035		0.084
Indicator individual lives in state in lowest wage/earnings quintile	--			-0.191		0.098	--			-0.311		0.186
Indicator firm size is small (<25 employees) (ref = 100+ employees)	--			0.234	***	0.058	--			--		
Indicator firm size is medium (25-99 employees)	--			0.151	*	0.069	--			--		
Indicator firm size is missing	--			1.593	***	0.472	--			--		
R-squared	0.071			0.111			0.034			0.054		
N	5,059			5,059			1,457			1,457		

*** indicates p<.001; ** indicates p<.01;* indicates p<.05.

Source: Authors' calculations from SIPP matched to DER, SER, and Numident.

Notes: Endnote 18 has information on state earnings rankings.

Table A2.8: Logistic Regression Models for Whether Workers' Earnings are Greater than Taxable Maximum at Ages 30 to 67, Pooled 1984, 2004, and 2008 SIPP Panels

	Just demographic characteristics			Include job characteristics		
	coefficient		SE	coefficient		SE
Intercept	-9.041	***	0.419	-10.849	***	0.451
Demographic characteristics						
Age	0.253	***	0.018	0.171	***	0.019
Age squared	-0.003	***	0.000	-0.002	***	0.000
Foreign born indicator (ref = native born)	0.287	***	0.072	0.959	***	0.083
Foreign born indicator * country of origin is less developed	-0.470	***	0.089	-0.383	***	0.094
Female indicator (ref = male)	-0.884	***	0.087	-0.776	***	0.091
Indicator education < high school (ref = high school graduate)	-1.438	***	0.184	-0.849	***	0.188
Indicator education college graduate or more	2.144	***	0.038	1.573	***	0.042
Unmarried indicator	-0.647	***	0.059	-0.576	***	0.062
Unmarried female indicator	0.595	***	0.093	0.425	***	0.097
Indicator has one or two children (ref = no children)	0.282	***	0.057	0.247	***	0.060
Indicator has three or more children	0.472	***	0.063	0.454	***	0.067
Indicator data on number of children is missing	0.655	***	0.110	0.490	***	0.117
Female * indicator has one or two children (ref = no children)	-0.645	***	0.095	-0.463	***	0.099
Female * indicator has three or more children	-1.068	***	0.117	-0.760	***	0.122
Female * indicator data on number of children is missing	-0.588	**	0.200	-0.367		0.209
Indicator race is black	-0.850	***	0.085	-0.731	***	0.088
Job characteristics						
Best estimate of annual hours		--		0.029	***	0.001
Total years in the OASDI-covered labor force		--		0.074	***	0.004
Indicator current occupation is managerial (ref = production or repair)		--		1.738	***	0.071
Indicator current occupation is professional		--		1.349	***	0.071
Indicator current occupation is sales		--		1.132	***	0.081
Indicator current occupation is clerical		--		0.362	***	0.109
Indicator current occupation is service		--		-0.449	*	0.178
Indicator current occupation is operator		--		-0.719	*	0.287
Indicator current occupation is farm/forest/fisheries		--		-0.563		0.305
Indicator current occupation is construction		--		0.205		0.150
Indicator current industry is finance (ref = all others)		--		0.510	***	0.059
Indicator current industry is professional/scientific				0.399	***	0.046
Indicator individual lives in a metropolitan area		--		0.816	***	0.063
Indicator metropolitan status is missing		--		0.900	***	0.093
Interaction terms for 1984 panel: demographic						
1984 panel indicator variable	-2.237	**	0.847	2.258	*	0.963
Age	0.124	***	0.037	-0.073		0.043
Age squared	-0.001	**	0.000	0.001	*	0.000
Foreign born indicator (ref = native born)	-0.208		0.129	-0.371	*	0.149
Female indicator (ref = male)	-1.381	***	0.335	-0.885	*	0.348
Indicator education < high school (ref = high school graduate)	0.541	*	0.230	0.177		0.237
Indicator education college graduate or more	-0.785	***	0.082	-0.683	***	0.093
Unmarried indicator	0.124		0.115	0.194		0.123
Unmarried female indicator	0.438		0.247	0.177		0.255
Indicator has one or two children (ref = no children)	-0.029		0.154	0.062		0.164
Indicator has three or more children	-0.258		0.160	-0.206		0.171
Indicator data on number of children is missing	-0.567	**	0.175	-0.323		0.187
Female * indicator has one or two children (ref = no children)	-0.042		0.392	-0.030		0.402
Female * indicator has three or more children	0.018		0.439	0.374		0.452
Female * indicator data on number of children is missing	0.347		0.382	0.398		0.395
Indicator race is black	-0.688	**	0.233	-0.449		0.240
Interaction terms for 1984 panel: job characteristics						
Best estimate of annual hours		--		-0.001		0.003
Total years in the OASDI-covered labor force		--		0.028	**	0.009
Indicator current occupation is managerial (ref = production or repair)		--		-0.106		0.124
Indicator current occupation is professional		--		0.084		0.133
Indicator current occupation is sales		--		-0.257		0.142
Indicator current occupation is clerical		--		-0.313		0.243
Indicator current occupation is service		--		-0.357		0.359
Indicator current occupation is operator		--		0.497		0.357
Indicator current occupation is farm/forest/fisheries		--		-0.087		0.470
Indicator current occupation is construction		--		0.352		0.218
Indicator current industry is finance (ref = all others)		--		-0.342	*	0.135
Indicator current industry is professional/scientific		--		-0.846	***	0.106
Indicator individual lives in a metropolitan area		--		-0.189		0.105
Indicator metropolitan status is missing		--		-0.141		0.187
-2 * log likelihood	34,750.63			32,527.89		
Share earning over threshold	0.086			0.086		
N	75,649			75,649		

*** indicates p<.001; ** indicates p<.01;* indicates p<.05

Source: Authors' calculations from SIPP matched to DER, SER, and Numident.

Note: Sample is restricted to individuals who report an average of at least 5 hours per week of work.

Table A2.9. Distribution of Total Years over the Last 20 Years over 4.5 Times the Average Wage Index for Individuals Ages 30 to 67, by Age and Sex, 2004 and 2008

		Distribution among those earning above 4.5 times the average wage at least once		
	None	1–3	4–7	8 or more
Men				
30–44	0.948	0.58	0.25	0.17
45–49	0.914	0.47	0.22	0.32
50–54	0.906	0.40	0.19	0.41
55–59	0.895	0.44	0.17	0.39
60–67	0.892	0.42	0.20	0.38
N	40,4963		3,100	
Women				
30–44	0.988	0.66	0.24	0.10
45–49	0.981	0.42	0.33	0.25
50–54	0.981	0.58	0.20	0.22
55–59	0.982	0.55	0.17	0.28
60–67	0.986	0.62	0.14	0.24
N	45,402		650	
All				
30–44	0.969	0.60	0.25	0.16
45–49	0.949	0.46	0.24	0.30
50–54	0.946	0.43	0.20	0.37
55–59	0.941	0.46	0.17	0.37
60–67	0.942	0.44	0.19	0.36
N	82,148		3,750	

Source: Authors’ calculations from 2004 and 2008 SIPP matched to DER, SER, and Numident. Sample weights account for probability of matching to the administrative data. Sample excludes imputed other-than-legal immigrants.

Notes

[1] Throughout our report, we use the terms Social Security and OASDI interchangeably. When we wish to discuss a specific OASDI component, like survivors insurance, rather than the program as a whole, we do this explicitly.

[2] We define these higher earnings as those that exceed 4.5 times the average wage—about $209,200 using the projected AWI for this year, well above 2013's current law taxable maximum of $113,700. Aggregate data from SSA's Office of the Actuary suggest that in recent years the share of workers who earned over this threshold ranged from about 1.0 to 1.5 percent. This is also a convenient level, as it is falls just about $20,000 below the estimated level where 90 percent of earnings would be taxable in 2013 (SSA 2012c), and several OASDI solvency plans incorporate a provision to return the taxable maximum to the level where it would achieve this ratio.

[3] The version of the model that we examine, MINT7, is still under development, so all estimates in this paper are preliminary based on an intermediate release (dated July, 2013). SSA has heavily invested in dynamic microsimulation models that analysts now routinely use to provide policymakers with distributional analyses of proposed changes to Social Security. A particularly challenging aspect of developing these models is properly modeling earnings dispersion. Examining fine measures, including year-to-year earnings variance, helps to validate these models. Correction of any observed deficiencies could strengthen the models' ability to analyze many prominent proposals, including removing the taxable maximum or surtaxes beyond certain earnings thresholds.

[4] About 6.4 percent of the labor force is not covered by Social Security (United States Senate 2010, table 1). These workers predominantly hold state and local jobs covered by a separate pension. Other uncovered workers include railroad workers, some students, and federal workers hired before 1984. One interesting anomaly under current law is that the taxable maximum does not increase in years in which a Cost-of-Living Adjustment is not applied to benefits due to low price inflation, even in cases when there was significant wage inflation.

[5] For convenience, we also refer to the taxable maximum as the "cap."

[6] This exclusion does not apply to earnings that are deferred into 401(k)-type plans, on which working individuals must pay Federal Insurance Contribution Act tax or, if self-employed, Self-Employment Contributions Act, as Social Security payroll taxes are formally known.

[7] For example, a value of 9,999,999 may indicate missing data, rather than earnings of nearly $10 million.

[8] Other microsimulation literature that focuses on modeling earnings includes Nakamura and Nakamura (1985) and O'Donoghue, Leach, and Hynes (2009). Other dynamic models recently used for policy analysis include Gokhale (2010)'s Demsim and Policy Simulation Group's GEMINI and SSASIM (see, for example, U.S. GAO 2001, 2004).

[9] In most analyses, we use single cross-sections of SIPP data—for example, cross-sections in 2004 and 2009. As a general rule we use a single observation to avoid double counting individuals and to facilitate disclosure review.

[10] The 1996 panel followed individuals for up to four years, while the 1984, 2001, and 2004 panels followed respondents for up to three years. Twelve waves (equal to three years) of 2008 SIPP data have been released as of July 2013. The 2008 panel starts by asking about mid-year (May through August, depending on rotation group) characteristics, while the others start near the beginning of the year (September through January, again depending on rotation group). For this reason, data from the 2008 SIPP sometimes refer to calendar year 2009, rather than calendar year 2008, and we label them accordingly.

[11] OASDI law did not determine the taxable maximum in the same way prior to 1994. In 1965, for example, nearly half of men (49 percent) earned over the cap.

[12] SIPP oversamples low-income households likely to participate in transfer programs, in contrast to a survey like the Federal Reserve's Survey of Consumer Finances (SCF), which makes special efforts to get sufficient samples of high wealth households (see, for example, Kennickell 2009 on the challenges of reaching high wealth holders). The SIPP weights account for oversamples, but may not adequately deal with the missing high earners.

[13] We compute these probabilities using SIPP panel-specific logistic regressions that include key economic and demographic covariates associated with the probability of matching to the SER. This approach assumes that the earnings of non-matched cases resemble their matched counterparts. While this assumption is strong, we believe our approach is preferable to ignoring the non-match bias (for example by excluding such cases).

[14] Our previous analyses suggested that patterns in total years of earnings and Average Indexed Month Earnings in MINT were satisfactory, so we focus here on more subtle aspects of lifetime earnings.

[15] Workers no longer need to accrue earnings in distinct calendar quarters to earn further OASDI covered quarters.

[16] As endnote 11 discusses, we chose the twenty-year threshold because the maximum was much lower in real terms in many years, so more workers exceeded the cap even if their earnings were not relatively high. Also DER earnings amounts are not reliable until about 1983, so we can only tabulate as far back as about 28 years from the present.

[17] We use a cutoff of 15,000 in international dollars for GDP per capita, based on based on World Bank (2010) rankings. This dividing line falls between Russia and Mexico, with Russia considered more developed and Mexico less developed. See Favreault and Nichols (2011) for detail.

[18] For the state earnings quintiles, we rank California, District of Columbia, Illinois, Maryland, Massachusetts, New Jersey, New York, Virginia, and Washington state in the top quintile. The bottom quintile includes Arkansas, Idaho, Iowa, Kentucky, Maine, Mississippi, Montana, South Carolina, South Dakota, and Vermont. We base these rankings on 2012 Bureau of Labor Statistics data on median wages and 2010 SSA earnings data.

[19] Approximately 13.3 percent of the labor force is employed by state and local governments. Just over three-quarters of these workers are covered by OASDI (U.S. Senate Special Committee on Aging 2010). Certain states and jurisdictions—for example, the District of Columbia, Maryland, and Virginia—have disproportionate shares of uncovered federal workers. So considering shares of state workers in isolation is imperfect.

[20] For example, New York state's share of uncovered state and local workers—3 percent—is below the national average of 6.4 percent and the average share of earnings that OASDI covers is also below average, suggesting relatively high shares of total earnings in the state fall above the cap. Similarly, New Jersey has close to the average share of uncovered workers but well below the average share of earnings covered. In contrast, Alabama and Mississippi have about average shares of uncovered workers but above average shares of earnings that OASDI covers, suggesting relatively low shares of earnings above the taxable maximum. Similarly, Nebraska's share of state and local workers who are uncovered equals the national rate, but the state's share of total earnings covered is above average, suggesting low shares of earnings over the cap.

[21] Occupation and industry are difficult to measure, as individuals may have multiple jobs in a year. We use occupation/industry in the first month of the calendar year where possible. If unavailable, we examine later months in the year. We consider both jobs and businesses (for the self-employed).

[22] Again, these outcomes pose measurement difficulties. For tenure and hours we look across multiple waves of the SIPP where possible to get the most accurate measure possible.

[23] We recognize that many of the variables in these regressions are correlated with one another and that many may be endogenous (e.g., people with high unobserved earnings capacity may select into high-earning occupations or move to certain regions). But the regressions can still provide some valuable descriptive information about the extent to which differentials across key groups remain after controlling for as many observables as possible (i.e., we can consider whether the effects for Hispanicity remain after we account for differential age structure and nativity or whether the effect for having children for women persists after we control for their experience and work hours).

[24] We use hours rather than earnings level because it can be viewed as somewhat exogenous. This restriction leads us to exclude about 8 percent of earners and about 3 percent of cases with earnings above the taxable maximum.

[25] For example, early years of the SIPP used traditional in-person interviews and paper surveys. SIPP, including the 2004 and 2008 panels, now uses computer-assisted personal interviewing for the first two interview waves and computer-assisted telephone interviewing. See Citro and Scholz (2009) for discussion.

[26] Liebman and Saez (2006) present similar distributions in order to explore the question of whether there is significant clustering at the taxable maximum because of the discontinuity in tax rates that occurs there. They find little evidence of such clustering.

[27] Figure A2.2 shows that while many earners who earn over the cap are clustered over the cap, total earnings over the cap accrue disproportionately to high earners, consistent with figure 3.

[28] This is a departure from our earlier analyses, where we use earnings in 2004 or 2009 to be consistent with the dates when we measure time-varying characteristics.

[29] Here, we choose the four covered quarters threshold, as we wish to indicate more significant attachment and because it appears commonly in various policy proposals.

[30] Estimates are sensitive to these two assumptions.

[31] This level is more symmetrical with our higher earnings threshold of 4.5 times the average wage than with the threshold of the taxable maximum, given the low prevalence.

[32] Although we would like to supplement these tables with survival analyses, data limitations (specifically, left censoring for earlier cohorts) prevented us from constructing survival curves.

[33] While we would prefer to use earnings deciles and smaller earnings breaks, the sample sizes in our data sets for some of the thin transitions (for example, from very low earnings to very high earnings) are too small to be reliable and meet privacy standards developed by the Census Bureau and SSA.

[34] The PIA is the benefit payable to a retired worker at the full retirement age.

[35] The rationale for the former choice is that the extra payments one receives make up for the reduced benefits, so one faces a tradeoff between having lower benefits for a longer period compared to higher benefits for a shorter period. The rationale for focusing on gross rather than net benefits is that it allows us to better understand where along the PIA formula earners lie. Extending these analyses to include taxes paid on benefits would be valuable for helping to better understand changes in wellbeing. Some experiencing reductions in replacement rates would experience corresponding reductions in personal income tax liability.

[36] Many proposals would pay partial benefits on these earnings, so our polar extremes (100 percent and zero) can serve to bracket options.

[37] Proposals that would raise the taxable maximum so that approximately 90 percent of earnings are covered include NCFRR (2010). Senator Tom Harkin introduced legislation in 2012 that would remove the maximum by 2022.

[38] These computations do not account for mortality differences. Everyone in our sample survived until at least age 62.

[39] The main difference between MINT and the SIPP matched data is that MINT imputes earnings records to those cases without a match to the administrative earnings records.

[40] Recall that about 6 percent of workers earn over the taxable maximum, compared to 20 percent in a quintile.

[41] Examples of policy analyses with MINT include Social Security Administration (2011), Iams, Reznik, and Tamborini (2009, 2010), Sarney (2008, 2010), Tamborini and Whitman (2010), and (Reno and Walker 2011).

[42] Within MINT, developers smooth across the seam between the splicing method and the regression method. In the age-education trajectory regression, developers use caps and then added noise back into the capped cases.