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PROJECTING LONGITUDINAL EARNINGS PATTERNS FOR LONG-RUN POLICY ANALYSIS

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Abstract

This paper presents a method for projecting person-level labor force participation and earnings for the U.S. population in a dynamic micro-simulation setting. A dynamic micro-simulation model starts with economic and demographic data for a current sample of the population, then stochastically "ages" that sample forward through time, ultimately generating a longitudinal micro data file, which is useful for studying Social Security and other long-term issues. The stochastic projections described here proceed in four steps: in each year, every person is sequentially assigned labor force participation, hours worked, unemployment spells, and earnings. The equations used to project the sequence of outcomes are designed to generate realistic cross-sectional and longitudinal heterogeneity, to capture cohort-level trends, and to be consistent with the underlying macro/policy environment in which the outcomes are projected. The projections suggest significant increases in the overall percentage of females in the labor force and the share of females working full time. Also, the relative earnings of lower-educated males are expected to continue declining, while the relative earnings of higher-educated females are projected to rise disproportionately.

1. Introduction

Imagine a longitudinal micro data file that contains individual earnings along with basic demographic variables such as age, sex, education, marital status, and marital pairings for a representative *future* sample of the population. Such a data set would be invaluable for analyzing solvency and distributional questions about Social Security and other long-run policy issues because the data file would have all the information needed to tabulate taxes paid and benefits received under any set of program rules. The goal of dynamic micro-simulation modeling is to produce a longitudinal data set like the one defined above. The role of this paper is to describe one set of building blocks for such a dynamic micro model: methods for predicting labor force participation and earnings.

A dynamic micro-simulation model typically starts with an actual micro sample of the population as of some base year, then "ages" that sample forward through time to generate the prospective longitudinal data set. The simulation process involves applying Monte Carlo techniques to a sequence of transition equations for each person in the model in each year of the simulation. These transition equations are effectively person-level probability distributions for demographic events (such as marital transitions and mortality) and economic events (such as labor force participation and earnings). Given demographic and economic outcomes for the micro sample, one can solve for the budgetary and distributional implications of various policies.

The methods presented here for projecting micro-level labor force participation and earnings are designed to accomplish several goals. First, the equations must be able to reproduce the observed cross-sectional and longitudinal earnings heterogeneity observed in historical data, which involves extending the partial earnings histories in the base micro sample and generating complete earnings profiles for people born during the simulation. Second, the equations must be able to capture cohort-level trends in labor force participation and earnings distributions and appropriately extend those trends forward through time. Last, the equations for labor force participation and earnings operate on a micro-sample of individuals, but the overall modeling context may require reconciliation between those individual outcomes and a specified macro/policy environment in which they are embedded.

The goal of generating reasonable cross-sectional and longitudinal heterogeneity is accomplished through a sequence of labor market transition equations. The first step determines which individuals participate in the labor force, the second step determines whether these individuals work full or part time, the third step assigns unemployment spells to those working, and the last step generates earnings outcomes as a function of the previously projected labor force outcomes. Each step is designed to capture both the cross-sectional and longitudinal variability for the process actually observed in historical data. As will be shown, those goals are consistent with introducing substantial random, or unexplained, variability in labor force participation and earnings across people *at any point* in time along with strong correlations between actual labor supply and earnings outcomes for any given person *over time*.

The same equations that are used to capture cross-sectional and longitudinal heterogeneity must also be capable of reflecting cohort-level trends observed in the data. For example, labor force participation of women has risen dramatically by cohort, so it is inappropriate to use the labor force participation of today's older women to project participation for future cohorts of older women. Similarly, there have been marked changes in the relationship between men's and women's earnings, and changes in relative earnings across education groups (especially for men). Earnings equations are estimated with cohort terms and cohort by education interaction terms (in addition to the expected life-cycle-related age terms) in order to capture these trends.

A final design goal for the labor force and earnings equations described here is to maintain consistency between the simulated longitudinal sample and the underlying macro/policy environment in which the micro model may be embedded. One implication of micro/macro consistency is that person-level earnings are specifed in relative terms; the dynamic micro equations generate individual earnings outcomes, which are then multiplied by a wage index in order to solve for total earnings.

The discussion thus far has ignored the fact that there are no existing public-use longitudinal data files suitable for use as the base sample in a dynamic micro-simulation model. The results presented here are based on an administrative data set maintained by the Social Security Administration, the Continuous Wage History Sample (CWHS). The CWHS contains high-quality earnings data and basic demographics for a 1 percent sample of the population for 1951 through 1998.[1] Remaking that data set into the dynamic model base file requires imputing various demographic characteristics, reconciling differences between the administrative data and various survey data sets used in the estimation, and performing a "historical" simulation ,which ages the sample through the current year for which aggregate and budgetary data are available (currently, 2001).

Applying the preferred specifications for the labor force participation and earnings equations to this micro base sample leads to several interesting predictions. Because estimated cohort differences at younger ages affect labor force participation of those groups as they get older, the projections suggest significant increases in the overall percentage of females in the labor force and the share of females working full time. Also, the relative earnings of lower-educated males are projected to continue declining, while the relative earnings of higher-educated females are projected to rise disproportionately. Those earnings projections are also the result of extending the identified cohort effects across age groups and time.

2. Projecting Individual Labor Force Participation and Hours Worked

The projection of individual earnings begins with the projection of individual labor supply, modeled in three sequential steps. The first step models labor force participation, which depends on demographic variables such as age, sex, birth cohort, and marital status, along with lagged labor force participation (to preserve longitudinal heterogeneity) and Social Security beneficiary status. The second step models part- versus full-time employment, which also depends on basic demographics and lagged values. In both the participation and hours equations, the approach is to estimate separate logit equations by age and sex in order to capture changes in participation across time and cohorts while simultaneously allowing variables like marital status

[1]The 2000 CWHS file has recently been released, which extends the sample collection an additional two years. The CWHS is not a public-use file but has been made available to the CBO through an agreement to carry out work that advances the study of Social Security.

to have effects that differ by age and sex. The final step in the labor supply projection is to assign unemployment spells to people in the labor force.

Labor Force Participation

Over the past 20 years, starkly different labor force participation trends have been observed for males and females. Figures 1 and 2 plot labor force participation rates by five-year cohorts for males and females based on pooled cross-sections of the March Current Population Survey (CPS). These labor force participation rates are the share of the population in the CPS who worked at least two months in the previous year. Older males, 50-70, are working at lower rates and more-recent cohorts of male teenagers are also working less while middle-aged females, 25-49, are working at higher rates. In particular, the dip during child-bearing ages is less pronounced for more recent cohorts of females. Projecting how these cohort-level trends will continue is a key hurdle for the labor force participation model.

The probability an individual of a given age and sex works is estimated using a logit equation estimated on pooled cross-sections of 16- to 90-year-olds from the March CPS, 1966-2001. Covariates include marital status, Social Security beneficiary status, lagged labor force participation, cohort effects, and a time trend. Rather than fit one participation equation for all age groups, a flexible econometric specification is used because there is no single statement about time/cohort effects that describes what is happening at all ages. The one distinguishing feature for both men and women is the existence of the hump-shaped age profiles, but the exact shape has evolved over time. It is clear that flexibility across both age and cohort dimensions is crucial. One would not, for example, want to impose a cohort or time effect that is proportional across all age groups because labor force participation rates have actually moved in different directions along the age dimension. Similarly, introducing broad age groups in the specification will not capture the interesting curvature of the underlying rates across age groups. Using a polynomial in age to capture the curvature of the transition probabilities by age would impose the same effect from the other control variables by age. But it is apparent that cohort/time effects will vary with age, and it is also likely that the effect of some control variables (marital status or lagged labor force participation) will vary across age groups.

The econometric approach used here can be thought of as an "age-centered" estimation technique that is an extension of the group-based approach used by other models. A separate participation equation is estimated for each single year of age and sex group, but the sample used for each equation actually includes every observation within a fixed age band around that point. For example, the estimation for males aged 25 includes all males ages 21 through 29, although the observations farther from the center are weighted less. As a further control, age itself is actually one of the variables used in the estimation. This approach has the desirable aspect that the effect of every other control variable (marital status, Social Security beneficiary status, lagged labor force participation, and cohort/time effects) is allowed to vary with age (which would be true with separate equations for each age group) but does not suffer from small sample size problems (which would occur if single equations were estimated for each individual age).

Although the CPS is not a longitudinal data set, it can be used to model labor force participation as a function of lagged labor force participation because the March supplement asks questions about work in the week previous to the survey and in the previous year. Thus, the dependent variable is an indicator for whether the individual worked in the previous week, while the lagged variable is an indicator for whether the individual worked at least two months in the previous year. As one may guess, estimated labor force participation rates differ using these two measurements. "Working last week" in the CPS is similar to the Bureau of Labor Statistics' labor force participation rate measure that is the average of monthly participation rates. "Working last year" in the CPS is similar to the covered worker labor force participation rate measure in the CWHS that is the total of all workers divided by the population. In the CWHS, an individual is designated as working if he or she earned $101 or more in 1993 dollars during the year. The covered worker concept counts a teenager who worked 10 weeks in the summer equivalent to a full-time, full-year worker, whereas the BLS concept would only capture the teenager in three monthly rates, and thus counts him or her as only one-fourth of a worker relative to a full-time employee. Thus, an equation estimating the probability of working last week will project fewer workers than is suggested by the covered worker concept in the CWHS.

To reconcile the conceptual differences between the CPS and the CWHS, calibration factors are used. These calibration factors equal the average difference in the labor force participation rates by age, sex, and marital status observed in the CWHS data and the rates predicted in the CWHS using the CPS equation for the most recent three years of data in the CWHS. As expected, the values of these calibration factors are, on average, positive, with the largest magnitudes for the youngest ages. In the projection, the applicable calibration factor is added to the predicted probability of working for each individual before the labor force assignment is made.

Unfortunately, even when comparing similar labor force concepts--the CPS "worked last year" to the CWHS "covered worker"--the two data sets historically produce different labor force participation rates by age. As can be seen in Figures 3 and 4, the CWHS has higher labor force participation rates for both male and female teenagers. The CPS has much higher rates for males during the prime working years. Older males in the CWHS also have lower reported labor force participation rates than in the CPS due to incomplete reporting of earnings for workers not covered by the Social Security system in the earlier years of the CWHS. Because the model employs lagged labor force participation in the projections, the underlying data differences cause stark adjustments in the early years of the projections. As will be seen later, higher participation rates are projected for ages 25 through 40 as the young cohorts observed in the CWHS reach middle age.

Coefficients for the labor force participation projection equations are shown in Tables 1 and 2, with statistically significant coefficient estimates indicated by **BOLD**. As mentioned, there is both a constant and age coefficient for each single year of the age group, which at first blush seems odd, but makes sense in the context of the age-centered approach. The age coefficient is an estimate of the slope of the probability function at that age, but it may make more sense to think of the actual simulation "constant" that applies to everyone of a given age as the estimated constant term plus the age coefficient times the value of the age.

The time trend is turned off for the projections. As noted in the tables, the cohort terms are carried forward at each age based on the most recent cohort observed in the March CPS. This does not capture the possibility that cohort trends observed at younger ages could provide information about how those same cohorts may react at older ages. However, with lagged labor force participation as a covariate, any higher or lower rate for working at the youngest ages gets carried through the entire lifetime for the individual. As Tables 1 and 2 indicate, the explanatory power of lagged labor force participation outweighs the time and cohort trends with coefficients of much greater magnitude across all ages and ubiquitous statistical significance. Thus, lagged labor force participation is key to capturing the changing participation rates over observed cohorts as they age.

Labor force participation is projected for each person in the base file by comparing a random draw with the computed probability of working. In the dynamic micro-simulation, the individual labor force participation decision is made after demographic transitions, including any marriages, divorces, or spouse deaths, and after benefit claiming decisions, including Disability Insurance incidence and Old-Age Insurance claiming. This sequencing is important, since current marital status and Social Security benefit status are covariates in the labor force participation equation. Once the fertility module is more sophisticated and new babies are assigned to mothers, the presence of a young child in the household will also be a key covariate driving labor force participation.

Full-Time Versus Part-Time Hours

Similar to trends in labor force participation, full-time work has been increasing for young and middle-aged women and decreasing for older men. Figures 5 and 6 present the share of the population working full-time (conditional on working at all) by five-year cohorts from the Panel Study of Income Dynamics (PSID). Overall, the pictures look similar to Figures 1 and 2, suggesting the same "age-centered" modeling technique as was used for the labor force participation decision can be used to model the full-time work decision.

Since the CPS does not collect current and lagged annual hours worked, it is necessary to switch to the PSID to estimate the hours model. The probability of working full time is estimated using a sample of working individuals ages 16 to 90 in the 1968 through 1992 waves of the PSID. The sample is limited to those observations with data on hours worked in the previous year, including those with zero lagged hours. The dependent variable for the logit estimation is an indicator for whether the individual worked full time in the current year. Individuals reporting 1,750 or more hours annually, a minimum of 35 hours for at least 50 weeks, are considered full-time workers.[2] Part-time workers include those working full-time hours for only part of the year (e.g., 40 hours for 26 weeks) and those working part-time hours for the full year (e.g., 20 hours for 52 weeks). Covariates in the full-time logit equation include age, martial status, lagged labor force participation, lagged full-time status, and birth cohort.[3] The two lagged variables identify separate effects for people who did not work last year, worked part-time last year, or worked full-time last year. Tables 3 and 4 show the coefficients by sex and age, with the statistically significant coefficients in **BOLD**.

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[2]This part-time hours definition accords with the definition used by the Bureau of Labor Statistics. Hotchkiss (1991) empirically estimates the employer-perceived cut-off between part-time and full-time work on separate samples of males and females as 38 hours. When she divides the sample by occupational category, the full-time hour cut-offs range from 31 to 40.

[3]Note that the PSID equations cannot estimate 1980 cohort terms since the data used only extend to 1992.

Similar to labor force participation, cohort terms are carried forward at each age based on the most recent cohort observed in the PSID. This extension does not capture the possibility that cohort trends observed at younger ages could provide information about how those same cohorts may react at older ages; however, with lagged labor force participation and full-time status as covariates, any higher or lower rate for working full time at the youngest ages is carried forward as the cohort ages.

Full-time work is assigned in the projections by comparing a random draw with the computed probability of working full time for each person assigned to be in the labor force. The full-time/part-time assignment is important for two reasons, projecting total hours worked and assigning earnings. For the former, it is not enough to assign whether individuals will work full time or part time, hours worked must also be assigned. Currently, hours are assigned in a static manner. All full-time workers are assigned 2,080 annual hours (40 hours a week for 52 weeks), which is actually lower than the average hours reported by full-time workers in the March CPS. All part-time workers are assigned the average part-time hours by age and sex reported in the March CPS for the previous year, covering the period 1984 to 1998. As seen in Figure 7, measurable differences exist between average part-time hours worked by age and sex. Both male and female part-time workers report more hours during middle age, with males reporting more hours than females at all ages. Average hours reported for age 71 is the average over ages 71 to 90 and is assigned to any part-time worker above age 70.

After a slight rise in the first 10 years, the micro model projects average hours worked will remain flat, at around 1,660 hours (see Figure 8). This is not surprising since annual hours worked by age and sex are fixed throughout the projection, and thus average hours worked in the micro-simulation will only change due to a shift in the distribution of full-time and part-time workers or a shift in the age/sex composition of the population. The model includes the capability to target a change in the growth of average hours worked, such as the 0.1 percent drop in average hours projected by the OASDI Trustees in 2002. This targeting of average hours is carried out by applying an adjustment factor to all predicted probabilities of working full time. In the case of targeting a drop in average hours worked, the adjustment pushes marginal full-time workers (those whose random draw falls just above the unadjusted probability) into part-time status, which one would expect to be driving any drop in average annual hours worked in the economy.

Unemployment Spells

The final step in the labor force projections is the assignment of unemployment spells. Unemployment is modeled very simply; the aggregate unemployment rate (determined by the underlying macro model) is targeted by assigning a corresponding number of unemployment spells based on an estimated relationship between the aggregate unemployment rate and the number of unemployment spells reported in the CPS.[4] The fraction of people experiencing spells is almost twice as large as the aggregate unemployment rate; an unemployment rate of 5.5 percent suggests 10.5 percent of the working population will experience an unemployment spell.

[4]Each person in the CPS is recorded as having at most one unemployment spell during the year if he or she reports one or more weeks looking for a job or on a layoff.

In addition, approximately two-thirds of unemployment spells are experienced by full-time workers, according to the CPS. Thus, after the number of spells is determined, the spells are randomly allocated over the workers based on full-time/part-time status.[5]

It is assumed that unemployment occurs in increments of 13 weeks, or 1/4 of a year. This assumption is slightly less than the 15-week mean unemployment duration found in the CPS over 1994-2000 (Abraham and Shimer, 2001). An individual assigned to experience an unemployment spell has his or her hours, and thus earnings, reduced by 25 percent. In reality, some individuals are unemployed for an entire year, while others are unemployed for only a few weeks. Assuming that everyone experiences roughly the average length unemployment spell will not affect total hours worked, a key variable for the macro model. However, this simplifying assumption reduces the effects of heterogeneous labor force experiences on earnings. Future work will change the unemployment model to a random assignment of unemployment spells for all working individuals as a function of age, sex, education, marital status, part-time/full-time employment status, lagged earnings, tenure, private pension plan coverage, and information on previous unemployment spells. As a part of this new model, heterogeneous lengths for unemployment spells will also be introduced.

3. Projecting Individual Earnings

Given projections of labor supply for the micro sample, the next step is to assign earnings. The approach starts with standard equations that project full-time-equivalent earnings based on control variables like age, sex, education, and cohort. These earnings equations are able to capture trends and compositional effects, yet are still consistent with the underlying macro/policy environment because the individual earnings measures are all *relative* to an overall wage index. One key to using this approach for micro-simulation is to explicitly consider the idiosyncratic component of earnings. Essentially, the significant unexplained variability in earnings is decomposed into "permanent" and "transitory" deviations from predicted values that evolve over time. In the simulation model, the two components are "shocked" in each year, generating the sort of longitudinal and cross-sectional variability observed in historical data.

Relative Earnings Across Cohort and Age Groups

Figures 9 and 10 present mean real earnings by five-year cohorts for males and females from the PSID. Both sexes exhibit hump-shaped age-earnings profiles reflecting changing wages and changing hours, with males peaking at much higher mean values. Similar to the rising labor force participation and full-time employment status, mean earnings are also rising for more recent cohorts of females.

As noted above, the micro model projects relative earnings or real, full-time-equivalent (FTE) earnings. Four adjustments are applied to the nominal earnings available in the PSID to derive the real, FTE person-level earnings used in the estimation. The first two adjustments remove the effects of inflation and productivity. First, earnings are converted to 1993 dollars

[5] The complete array of labor force participation values in the micro model is 0=out of the labor force, 1=part time, unemployed, 2=part time, not unemployed, 3=full time, unemployed, and 4=full time, not unemployed.

using the consumer price index for urban wage earners and clerical workers, the CPI-W.[6] Second, earnings are adjusted to 1993 productivity levels using an index that accounts for historical real wage growth. Removing the aggregate component of earnings growth for individual earnings is consistent with an environment in which the macro sector generates overall average earnings outcomes. In interpreting the estimates below, it helps to keep in mind that the ultimate goal is to predict the *distribution* of earnings across a population (cross-sectional and longitudinal) as opposed to trying to predict earnings levels of particular individuals at particular points in time. Still, it is important to note that adjusting longitudinal earnings for aggregate price and productivity does not necessarily mean that earnings distributions are stable over time.

The third and fourth adjustments create FTE earnings values, and thus only affect earnings of part-time workers. As noted above, anyone in the PSID reporting less than 1,750 annual hours of work is designated part time. The third adjustment multiplies earnings for part-time workers by the ratio of full-time hours (2,080) to hours worked in part time. In anticipation of the method for assigning hours in the projections, PSID earnings are adjusted using the average part-time hours by age and sex observed in pooled cross-sections of the March CPS (see Figure 7).

The fourth adjustment accounts for the full-time wage premium, i.e., higher wages paid to those working full time.[7] The literature has documented a range for the full-time wage premium between 3 and 30 percent (Averett and Hotchkiss, 1996). Ehrenberg et al. (1988) estimate a wage differential of 18 percent using individual data from the 1984 March CPS. They also find negative and statistically significant probabilities of health insurance and pension coverage for part-time workers, which suggest even lower total compensation for those workers. Lettau (1994) estimates a 16 percent premium for full-time workers using a sample of earnings for employees working in the same job at the same establishment. Based on these estimates from the literature, a 15 percent discount is applied for those workers designated as part time.

Although not shown, the age-earnings profiles for FTE earnings from the PSID look similar to Figures 9 and 10, but as expected all levels are higher, particularly at the youngest and oldest ages, when part-time work is more prevalent.

Estimated Earnings Equations

Earnings equations are estimated for males and females ages 16 to 90 in the labor force using data from the PSID, 1968-1992. Log, real, full-time-equivalent earnings are regressed on age dummies and on age dummies interacted with an indicator for 14 or more years of education,

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[6]Alternatively, the CPI-X1 inflation index could have been used, giving different answers for the historical inflation adjustments. The CPI-W is used because that is the inflation measure used by SSA.

[7]Lettau (1994) discusses the theory behind the full-time wage premium. Possible explanations include endogeneity in the choice of part-time work among the least productive or dual labor markets where the bad jobs are disproportionately part time.

the minimum for a college degree.[8] Individuals attending college start full-time work at a later age and have steeper personal earnings growth, particularly during the first years of full-time work. Therefore, age-earnings profiles should differ markedly by education status. Murphy and Welch (1990) recognize both these points in their analysis of age-earnings profiles. They use different starting ages for accumulating labor market experience and document the different slopes of age-earnings profiles by education status. The PSID data confirm that age-earnings profiles differ by education status, where the coefficients on the age/education dummies are jointly significant with F-statistics of 76 for males and 42 for females.

Rising wage inequality by educational status dampened wage growth for males with lower education between the middle 1970s and early 1990s. Gohmann et al. (1998) compare age-earnings profiles between 1979 and 1989 for a split into four education statuses. They found that over the decade, real earnings actually dropped for workers with less than a college education. Additional research has also documented this phenomenon (see Katz and Murphy, 1992; Juhn, Murphy, and Pierce, 1993; Bound and Johnson, 1992). To capture this observed trend, 10-year cohort effects, and cohort effects interacted with high education status, are also included in the earnings equations. Similar to the labor force and hours modules discussed above, in the simulations the cohort terms are carried forward at each age based on the most recent cohort observed in the PSID.

Table 5 presents the coefficients for the earnings equations with separate columns by education status. The high-educated columns present the sum of the age (cohort) coefficient and the coefficient on the interaction of age (cohort) and education. Coefficients in **BOLD** reflect statistically significant interaction terms.

As discussed above, in the case of labor force participation, using an equation estimated on one data set to project future values on a second data set can be problematic. Although earnings in the PSID and the CWHS can be adjusted for the same price and productivity differences, because both data sets are samples of the population there is bound to be some difference in the distribution of earnings. Figures 11 and 12 present mean real earnings by cohort for males and females from the CWHS. Although similar to Figures 9 and 10, differences do exist, particularly in the slope of the profile over the youngest ages and the level of peak earnings. These differences are addressed in the projections through the use of calibrations, or mean error adjustments computed by comparing actual with predicted earnings for the base file. The recorded earnings in the 1998 CWHS are adjusted to FTE values using the four adjustments discussed above. Note that the CWHS historical data do not include information on hours worked, thus the third and fourth adjustments are weighted by the predicted probability of part-time employment, with the probabilities based on the hours model described in Section 2, that is:

[8] When possible, high-educated status was limited to those who reported an associate's degree or higher. Unfortunately, the PSID only reports years of education. It is possible that 14 years of education could reflect someone who dropped out of college without completing any degree, potentially biasing down the effect of a college degree in the earnings estimation.

$$fte\_earnings_{it} = actual\_earnings_{it} * prob\_full\text{-}time + actual\_earnings_{it} * (1\text{-}prob\_full\text{-}time) * (1/1.15) * (CPS\_average\_part\text{-}time\_hours(age,sex)_{it}/2080)$$

Using the equation coefficients estimated on the PSID, earnings are also predicted for individuals with recorded earnings for 1998 in the CWHS base file. The actual FTE earnings from the CWHS are then compared to the predicted FTE earnings. The measured differences, interpreted as the error from using the PSID to estimate an equation used to predict on the CWHS, are averaged by age and sex. These errors are relatively small, with log values ranging from 0.56 to -0.35 for prime working ages, with slightly larger magnitudes at ages above 70. The resulting FTE earnings mean error adjustments by age and sex are added to all future projections of earnings.

Modeling Idiosyncratic Earnings Differentials

In principle, the estimated earnings equations could be used to make individual earnings projections by simply adding an error term randomly drawn from the probability distribution of the equation residuals to the earnings prediction based on person *i*'s age, sex, birth year, and education. However, equations designed to capture the average effect of controls like age and education are not capable of generating individual earnings patterns with the desired amount of cross-sectional and longitudinal heterogeneity. In particular, individuals with actual earnings on either side of the predicted value tend to stay there in future periods. The desired heterogeneity can be generated by separately modeling the equation residuals as a time series; effectively, the idiosyncratic component of earnings is modeled after the predictable component is determined. In the approach here the idiosyncratic component evolves over time through a sequence of uncorrelated "permanent" and "transitory" shocks.

Specifically, log earnings are modeled as the sum of three pieces. The first is the predictable component, which is the mean for person *i*'s age/sex/education/cohort group from the estimated earnings equation. The second component is a "permanent" earnings differential for person *i* that measures how the expected difference between actual and predicted values tends to change slowly over time. Permanent earnings differentials evolve through a sequence of symmetric shocks designed to capture longitudinal heterogeneity. The third component is a "transitory" shock for person *i* that measures the difference between actual and predicted earnings. Because transitory shocks are not auto-correlated, they capture any residual variation in earnings that is not expected to persist over time. Both the permanent and transitory income shocks are specified as independent, identically distributed (i.i.d.) processes with an expected value of zero.

The decomposition of the difference between person *i*'s predicted and actual earnings into transitory and permanent differences has proved useful in other contexts in which the goal was to generate realistic earnings heterogeneity in a micro sample. The approach below follows closely the work of Carroll (1992) that focused on uncertainty about future labor income while studying consumption behavior in a stochastic setting. Alternative models of the earnings process can lead to different predictions about earnings patterns (and thus consumption and saving) but the permanent/transitory decomposition seems most realistic.[9] Decomposing earnings changes into permanent and transitory shocks is also consistent with the patterns of within-cohort earnings variation by age, as documented by Deaton and Paxson (1994).

In a micro-simulation, the approach of using permanent and transitory shocks involves an initial permanent earnings differential assignment for each individual, then a random draw of permanent and transitory shock values in each year. The value of the permanent shock determines movement in the permanent earnings differential over time, and the value of the transitory shock determines actual income. Because the earnings decomposition is modeled in logs, one can think of this as a ratio decomposition--the permanent earnings differential indicates the ratio of "potential" earnings to the mean for person *i*'s age/sex/education/cohort group, and the transitory shock applies a further ratio to determine actual (relative to potential) earnings.

The first step in building this type of earnings projection model is to estimate the variances for the permanent and transitory earnings shocks. Again, the approach that follows is based on the work of Carroll (1992). Given longitudinal data and an earnings equation, the estimation involves computing the actual residuals for every person at each age, then measuring the *changes* in error terms over time for each individual. If the errors were all positive or negative by the same amount at every age for every individual, there would be complete persistence in the earnings differential and both the permanent and transitory shocks would have zero variance. To the extent that equation residuals do vary over time, those changes can be decomposed into permanent and transitory movements.

Computing and averaging the variance of residual earnings changes for every individual in the longitudinal data file creates a vector of up to "m" period gaps, where $m+1$ is the number of years in the panel. For example, if three years of data are available, for each person there are two sets of one-year gaps (between periods one and two and periods two and three) and one set of two-year gaps (between periods one and three) that can be used to compute the variance terms. Using CWHS data for 1984 to 1998 yields up to 14 periods for earnings errors for each person. The variance of changes in the estimated equation residuals in the CWHS are shown separately for men and women in Table 6.

If movement in the idiosyncratic errors is consistent with both permanent and transitory shocks, the variance of changes in the earnings equation residuals will rise with the length of the gap because the changes further apart in time are more persistent. Indeed, for any two pairs of variances measured at distinct gaps, there are two known sample variances and two unknowns (the variances of permanent and transitory shocks) to solve for. The approach here is to follow Carroll (1992) and use all of the information from the 14 periods to generate more efficient estimates of the variance. The estimated variances are regressed on the length of the gap "m" where the slope term is the variance of the permanent shocks and the intercept (divided by two) is the variance of the transitory shocks. As Carroll (1992) points out, there is likely to be short-run correlation that would distort the decomposition, so the preferred approach is to fit the regression over gaps between periods three and 14.

Applying the Carroll (1992) methodology to the CWHS data yields estimates for the standard deviation of permanent shocks that are about 0.1 for men and 0.06 for women. The

[9] See, for example, Carroll (1997); Hubbard, Skinner, and Zeldes (1995); and Huggett and Ventura (2000).

estimated standard deviations for the transitory shocks are roughly 0.55 for men and 0.60 for women, but those are likely to be biased upward because of the unexplained widening of the earnings distribution in the 1990s. Therefore (after some experimentation) the actual values used in the simulations are 0.35 and 0.40. These differences between men and women are intuitive, because men's earnings disperse more as they move through the life cycle, and thus permanent shocks are quantitatively more important.

Before these permanent and transitory shocks can be used to project earnings, it is necessary to assign permanent earnings differentials to individuals in the micro base file (who have some earnings history) and to new individuals "born" into the model (specifically, those who have no actual earnings history). The key to understanding how initial permanent differentials are assigned is to consider the following: at any point in time, the overall variance of the earnings equation residuals is the sum of the variance of the permanent differentials and the variance of the transitory shocks. Within any given cohort, there is some initial or "base" dispersion of earnings differentials, which linearly grows as the cohort ages because of permanent shocks. It is straightforward to show that the overall variance for a sample (whose earnings have always been generated by these processes) is the sum of the base permanent differential variance, the permanent shock variance times the average age, and the transitory variance. Thus, the base variance is solved for by subtracting the other pieces.

The error variance decomposition described above is applied to the CWHS sample in Table 7. The overall variance of the earnings equation error terms is 0.9706 for men and 0.8582 for women. The average age term is measured relative to age 22 (where base earnings differentials are assigned to the sample to avoid the confounding effects of pre- and post-college jobs; for individuals aged 16 to 21, the error is assumed to be all transitory shock). Subtracting the estimated permanent and transitory components of earnings variation from the total yields estimates for the base permanent differential variance of 0.6454 for men and 0.6264 for women. That implies a significant amount of initial, unexplained earnings heterogeneity within every cohort. In a sense, that result is just a restatement of general conclusions about the sort of earnings equations used here: the equations show statistically significant effects of age, sex, education, and cohort on earnings, but the overall explanatory power of the equation (measured by the R-squared) is generally quite low.

Given the estimated variance of the base values for the permanent differentials, it remains to assign those differentials to actual observations. For new observations that have no earnings history, one simply draws a value from the distribution of permanent differentials (in practice, the model uses a bootstrap draw). For individuals with some earnings history as of the base period (1998), an inference about how much of their error is transitory and how much is permanent differential is needed. The approach is to assume (since transitory shocks are expected to be zero) that the actual error is an unbiased estimate of the permanent earnings differential. However, the overall variance of the permanent differentials has to match the variance derived above, so weights are applied to earnings equation errors to correct for differences and make the overall variances match.

The actual projections of earnings conditioned on labor force participation can now be summarized. In the first year that an individual is projected to work, an initial permanent earnings differential is assigned (or derived in the first year of the simulation if the individual has an actual earnings history). In that year and all future years, the predictable component of earnings is projected using the earnings equation, the permanent earnings differential is augmented by a randomly drawn permanent earnings shock, and the transitory shock is drawn for the current year. These three components are added to give predicted real, FTE earnings. The FTE earnings are then adjusted to actual earnings according to assigned labor force status (that is, scaled down if the person is part time and/or unemployed), inflation, and real wage growth.

4. Developing a Micro-Simulation Base File

The base longitudinal data file used for the micro-simulation described here is the Continuous Work History Sample. This data set, administered by SSA, contains longitudinal earnings information on a 1-percent stratified cluster sample of all people ever issued Social Security numbers, which translates into a sample size of roughly three million individuals with earnings reported for 1951 to 1998 (Smith, 1989). Each year, the entire sample is followed, recording OASDI and HI taxable earnings, total wages plus employee defined contribution plan deposits (starting in 1984), self-employment status, OAI and DI worker benefit entitlement, or death. In addition, new individuals are introduced to reflect the issuance of new Social Security numbers. This sampling structure makes for a truly unique longitudinal data set, where each annual cross-section represents 1 percent of the population with Social Security numbers.

The CWHS is preferable for use as a dynamic micro-simulation base file when compared to the available public-use cross-sectional or longitudinal files such as the CPS or PSID. Available cross-sectional data sets do not have the requisite longitudinal histories needed to project forward using dynamic micro-simulation.[10] The CWHS contains earnings records for each individual that span more than 40 years. Publicly available longitudinal data sets like the PSID are much smaller than the CWHS, and those data also suffer from recall bias and response problems for the highest-earning individuals. As an administrative data set, the CWHS has much better reporting of income for the entire earnings distribution.[11] The downside is that the administrative nature of the CWHS limits the demographic data to the information that is available on the initial Social Security Number application: year of birth, sex, and race.[12]

As noted in the discussion of labor force participation, one complication with using the CWHS as a micro base file but estimating projection equations using other survey data like the CPS is that the concept of labor supply differs. Labor force participation in the CWHS is a "covered worker" concept, such that positive earnings above $100 indicate an individual is

[10]An exception is the SIPP data file used by the SSA in its MINT model, which has linked earnings and Social Security claims and benefits information. The matched SIPP data still suffer from some of the problems mentioned with respect to the PSID–sample size and coverage of the earnings distribution.

[11]Since the CWHS was originally set up for administering Social Security, recorded earnings were truncated at the taxable maximum until the early 1980s. Imputations for earnings above the taxable maximum are made for the 1951-1983 period using data on the frequency each individual reports truncated earnings and targeting earnings distributions from the CPS. More details are available on request.

[12]Throughout the imputations and projections, race is not used because the information on the CWHS (collected when the Social Security Number was issued) is incomplete.

working. Many data surveys, such as the CPS, base labor force participation on reports of hours worked during the survey month or week. Therefore, discrepancies emerge in labor force participation rates, especially in age/sex groups for whom seasonal or part-time work is important. Table 8 shows labor force participation rates by age and sex, and the effect is pronounced for the youngest age groups. As discussed above, these discrepancies are controlled for with the use of calibration factors that align the CPS-based estimates with observed CWHS participation rates.

A second complication is the lack of information on hours worked in the CWHS. Therefore, part-time or full-time status is imputed in each year of the historical data as part of the preparation of the micro base file. Before that imputation is carried out, marital histories and education are imputed.[13]

Education, currently an indicator for 14 or more years of schooling, is imputed based on the earnings projections equations. Using the earnings equation described in Section 3, earnings are predicted under assumptions of both high and low education. These two predictions are subtracted from actual earnings, giving two errors based on the education assumption. The probability that an individual would have that observed error given each education status is computed using a cumulative normal distribution, with variance taken from the PSID equation results. These probabilities are averaged over all years the individual has earnings and normalized to give a measure of the probability of being high educated relative to the probability of being low educated. The average probabilities of being high educated are adjusted in order to target observed educational distributions by birth cohort from the CPS. A random draw from the uniform distribution over the unit [0,1] interval is compared to the individual's adjusted probability of being highly educated. High-educated status is assigned if the draw is less than the computed probability. Individuals without any recorded earnings are randomly assigned an education status based on the educational distribution observed in the CPS for the corresponding birth cohort.

Table 9 presents the share of high-educated males and females for various cohorts in the CPS and the CWHS imputations. Both sexes have experienced an upward trend in the share with a college degree, although the male share dipped for the 1955-1959 cohorts. Starting with the 1955-1959 cohorts, more females have high-educated status than do males. In the projections, all future cohorts are randomly assigned an education status at birth corresponding with the observed educational distribution for the 1965-1975 cohorts in the CPS.

Figures 13 through 20 present age-earnings profiles split by education status from the PSID and CWHS as a demonstration of how well the education imputation worked. Although it appears that the low-education imputation captured lower earners and the high-education imputation captured higher earners, the differences are not quite as stark as in the PSID data. Even though the education imputation relies on earnings, the ultimate assignment is still done based on a random draw compared to the probability of being highly educated. Another possible approach would be to assign the highest earners to high education status. This assignment would lessen the bias reported above but would remove the important heterogeneity found in real data, where some high-educated individuals earn less than some low-educated individuals.

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[13] See O'Harra and Sabelhaus (2002) for a discussion of the marital imputations.

Hours imputations are made using equations similar to the projections equations described in Section 2; however, actual earnings are included as a covariate. A time trend is also included to capture the rising share of both men and women who are working full time over the past few decades, where the trend for women was much greater. For everyone with positive labor force participation (i.e., reported real earnings of more than $100) the probability of having worked full time that year is computed based on a logit estimated on the PSID. For the first year of observed earnings for any individual (censored by data collection to 1951 for many in the sample), it is not possible to use lagged labor force participation or full-time status in the equation. Thus, the probability of working full time for the first observed year is based on age, sex, marital status, time, birth cohort, and log real earnings. (Note that age, time, and birth cohort effects can all be estimated since birth cohorts are 10-year dummies). Once an initial hours imputation is made, all further imputations are based on a logit equation including lagged labor force participation and lagged imputed full-time status.

The last consideration when working with the CWHS data file is that there will always exist a lag between the availability of the micro data and the first year of the integrated micro/macro model projections, or the first year for which aggregate data are not available. Micro labor force and earnings outcomes for those interim years are generated using the projection methods discussed above. Because aggregate data for labor force, hours, and earnings are known for those interim years, micro assignments for earnings, labor force participation, and hours are reconciled with those aggregates. This reconciliation is accomplished by solving for "alignment" factors that actually provide useful information--those values indicate how well the micro model is predicting "jump-off" values for labor force and earnings.

5. Properties of Simulated Earnings Trajectories

As noted in the introduction, the goal of this paper is to explain the methods used to generate longitudinal earnings for a *future* sample of the population in a dynamic micro-simulation context. Given the structure described above, the inputs to projecting micro earnings patterns include a base micro data file with economic and demographic information for a current sample of the population; a set of equations for labor force participation, hours worked, and earnings; and another set of transition equations that predict the independent variables that affect earnings (in this case, education, Social Security beneficiary status, and marital status). In the case of earnings, it is also important to introduce reasonable time-series properties for the error term so that the generated longitudinal heterogeneity is similar to that which exists in real data. All of those pieces together can be used to create long-term projections of earnings for a representative sample of the population.

The discussion below focuses on the micro labor force and earnings outcomes in history and a baseline simulation of the integrated micro/macro model. A complete description of the rest of the model is beyond the scope of this paper, but details can be found in Harris et al. (2002). Briefly, the macro environment is a standard neoclassical growth model in which average wage growth and interest rates are determined using simple first-order conditions and a Cobb-Douglas production technology. Although the trajectory of GDP growth is sensitive to choices about overall budget policy and private saving behavior (which together determine capital accumulation), the scenario here is intended to be fairly neutral. That is, overall economic growth is generally stable over the 75-year period, varying principally with changes in the labor force that result from changing demographics and the micro model described here.

The first set of results are labor force participation projections. Figures 21 and 22 present historical and projected labor force participation rates by age and cohort for males and females in the micro sample. For males, projections are quite steady over the cohorts. The estimates suggest a slight increase in labor force participation projected for ages 16 to 49. As noted in Section 2, this reflects a higher labor force participation rate observed for the 1976-1980 cohort at ages 16 to 19 in the CWHS that feeds through to later ages for that same cohort due to the lagged labor force participation rates, and all future cohorts due to the cohort effect. For the females, the increase in labor force participation rates at nearly all ages continues through the 1986-1990 cohorts, then levels off for future cohorts.

The shifts in labor force participation by sex and cohort have some important cumulative effects in lifetime labor force participation patterns, especially for females. Figures 23 and 24 show the number of years the current age 62 cohort spent in the labor force. The cumulative participation rates for males are not predicted to undergo much change. This is not the case for females, however. Only about 24 percent of females who reached age 62 in 2002 had worked 36 or more years. That share is expected to rise to over 60 percent for the groups reaching age 62 after about 2040.These projections are the direct effect of extending identified cohort-level differences (or lack of differences in the case of men) across age groups and time.

The second set of results are full-time versus part-time employment projections. Figures 25 and 26 present historical and projected full-time shares for the CWHS micro base file by sex and cohort. As with labor force participation, the projected share of males working full time is fairly steady over the cohorts, with a slight increase over the age 25 to 45 range. For females, the rising trend in the share working full time during child-bearing years is projected to continue through the 1990 cohort, then stabilize.

The final set of results are the earnings projections. There are several questions to be addressed when considering the earnings projections. First, how are average earnings within sex and education groups projected to change over time? Second, how are the percentiles of the annual earnings distribution projected to change? Finally, do the estimated equations and permanent/transitory shocks to earnings work together to preserve the desired levels of longitudinal heterogeneity? These questions are addressed in turn.

First, the models developed here suggest continued changes in average earnings across sex and education groups. Figures 27 to 30 show average earnings in history and projection periods by age, sex, cohort, and education status. It is important to keep in mind that the concept of "real" earnings in these graphs involves removing the effects of both inflation and average real wage growth; these are, in a sense, relative earnings normalized to 1993 dollars.

Figures 27 and 28 show average earnings for males, first the less than college group, then those with 14 or more years of education. The projections of relative average earnings for the low-educated males shows deterioration for future cohorts in their 30s, 40s, and beyond. That is the effect of carrying the cohort by education terms in the earnings equation forward through time. It is consistent with assuming that the declines experienced by less than college-educated males will continue in the future. Figure 28 shows that some of those relative losses are offset by the expected relative gains of high-educated males.

Figures 29 and 30 show historical and projected average earnings for females, again split by education status. Unlike males, the relative earnings of low-educated females are not expected to change much for future cohorts. (Again, one need only look at the cohort by education terms in the estimated equations (Table 5) to see why this is true.) Relative earnings of high-educated females in middle age and beyond are expected to rise for future cohorts, however, continuing the strong growth for recent cohorts at younger ages.

The second set of outcomes to consider are various percentiles of cross-sectional earnings distributions. Figures 31 and 32 show 1st, 5th, 25th, 50th, 75th, 95th, and 99th percentiles for men and women between 1984 and 2076. The trends show that the approach of extending cohort effects (but shutting off time trends) has modest effects on earnings cross-sections. Earnings for men and women at various points in the distribution show some continuation of trends in the forecast period, but generally the distributions stabilize near their current values. This outcome is also affected by the specifications for the idiosyncratic component of earnings; if the variance of the base permanent differentials or the permanent shocks increased over time, the percentiles of the cross-sectional earnings distribution would widen.

Given the stability in annual cross-sections, the next question to address is whether the model is able to capture the desired longitudinal heterogeneity in earnings patterns. Tables 10 and 11 show cross-tabulations of annual and lifetime earnings by sex for selected cohorts of 50-60-year-olds at various points in time. If every person's annual earnings decile always matched his or her lifetime earnings decile, the diagonal elements would be exactly 10 percent. The amount of variation in each person's earnings over his or her life is reflected in the off-diagonal terms. Starting in the top panel, which is based on actual CWHS earnings data from 1998, it is clear that there is significant variation in individual earnings in historical data. The other panels (for 2010, 2040, and 2070) show that the model is generally successful at replicating that variation in the projections, although there is some increased concentration in the joint distribution of annual and lifetime earnings at the lowest deciles.

Figure 33 reinforces the conclusion that the permanent and transitory shocks are creating the desired longitudinal heterogeneity. This figure plots the average variation in the difference between projected annual earnings over ages 16 to 59 for each individual and average earnings in the economy for the corresponding age, sex, and year, normalized by average lifetime earnings. If there were significant changes in the patterns of permanent earnings differentials in the projections, the overall variance would deviate from history, which is not the case. There is an unexplained spike in the amount of variation for the 60-year-olds in the early part of the projection period, but the variation quickly settles down to historical levels.

6. Conclusions

A key component in any dynamic micro-simulation model of the economy is the projection of longitudinal earnings. This paper presents methods for projecting individual labor force participation, hours, unemployment spells, and earnings, using the CWHS as the micro base file. The equations used to project the sequence of outcomes are designed to generate realistic cross-sectional and longitudinal heterogeneity, to capture cohort-level trends, and to be consistent with the underlying macro/policy environment in which the outcomes are projected. The projections suggest significant increases in the overall percentage of females in the labor force and the share of females working full time. Also, the relative earnings of lower-educated males are expected to continue declining, while the relative earnings of higher-educated females are projected to rise disproportionately.

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Figure 1. Male Labor Force Participation Rates by Age and Cohort, CPS 1965-2000

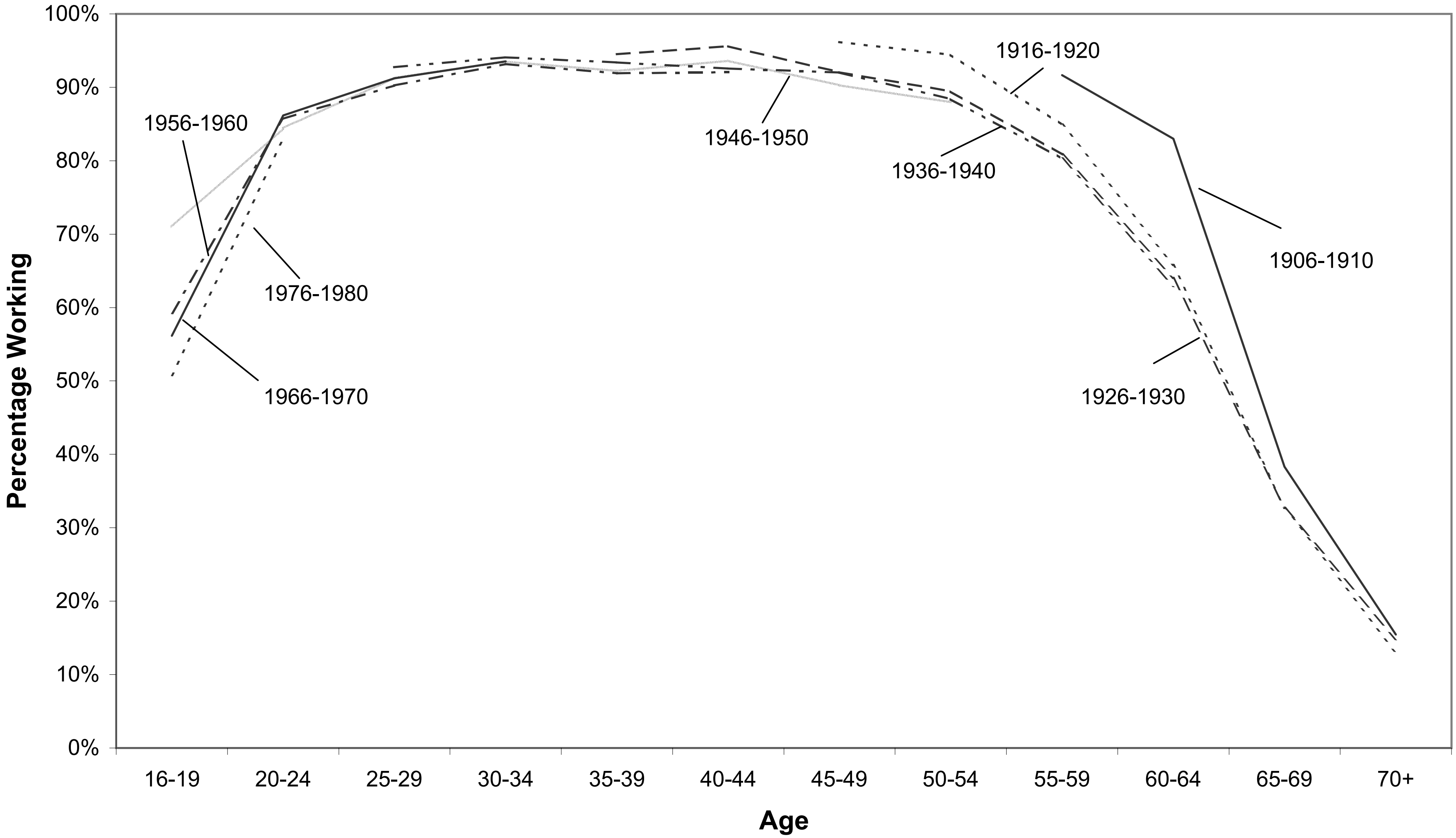

Figure 2. Female Labor Force Participation Rates by Age and Cohort, CPS 1965-2000

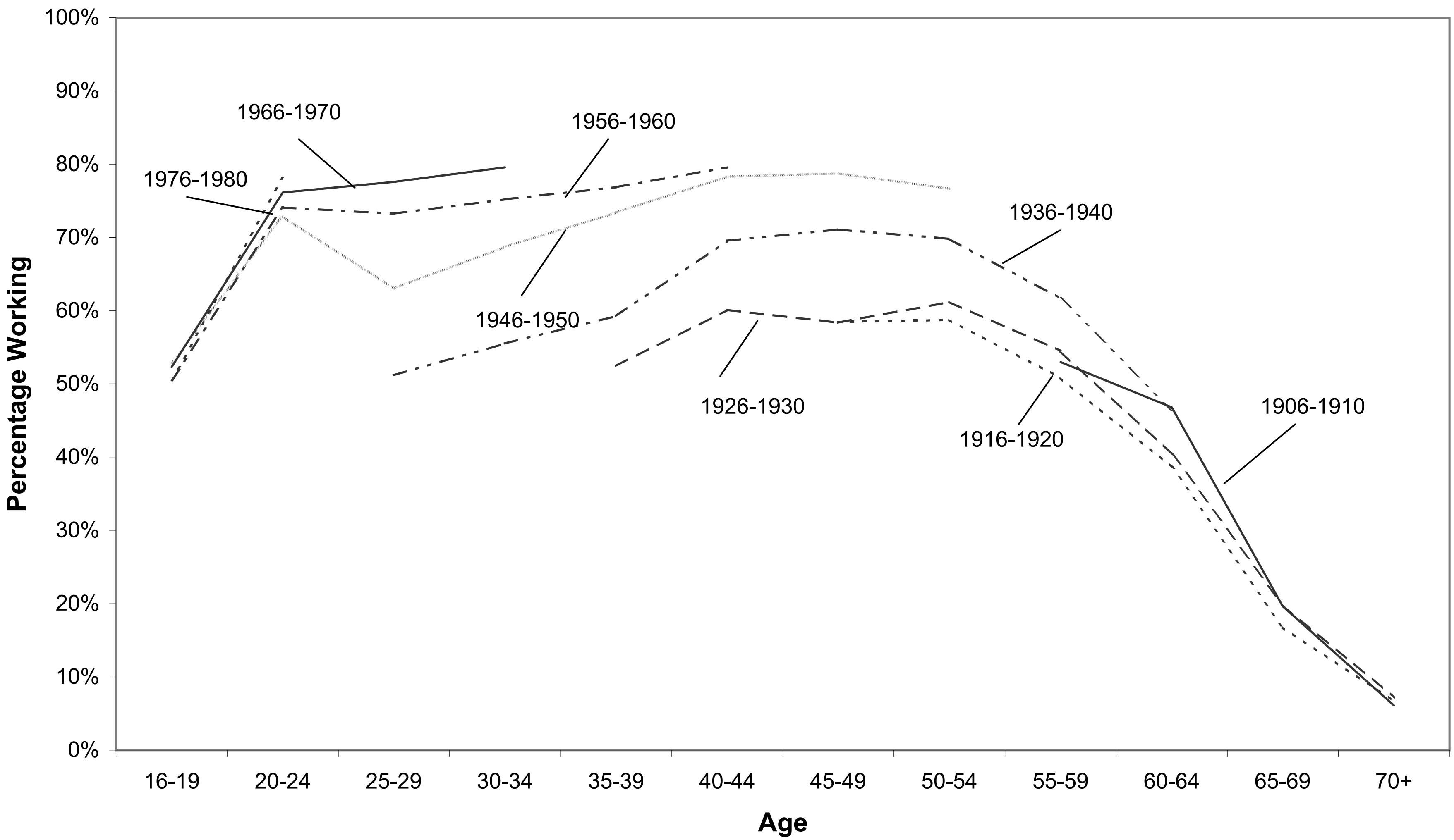

Figure 3. Male Cohort Labor Force Participation, CPS versus CWHS

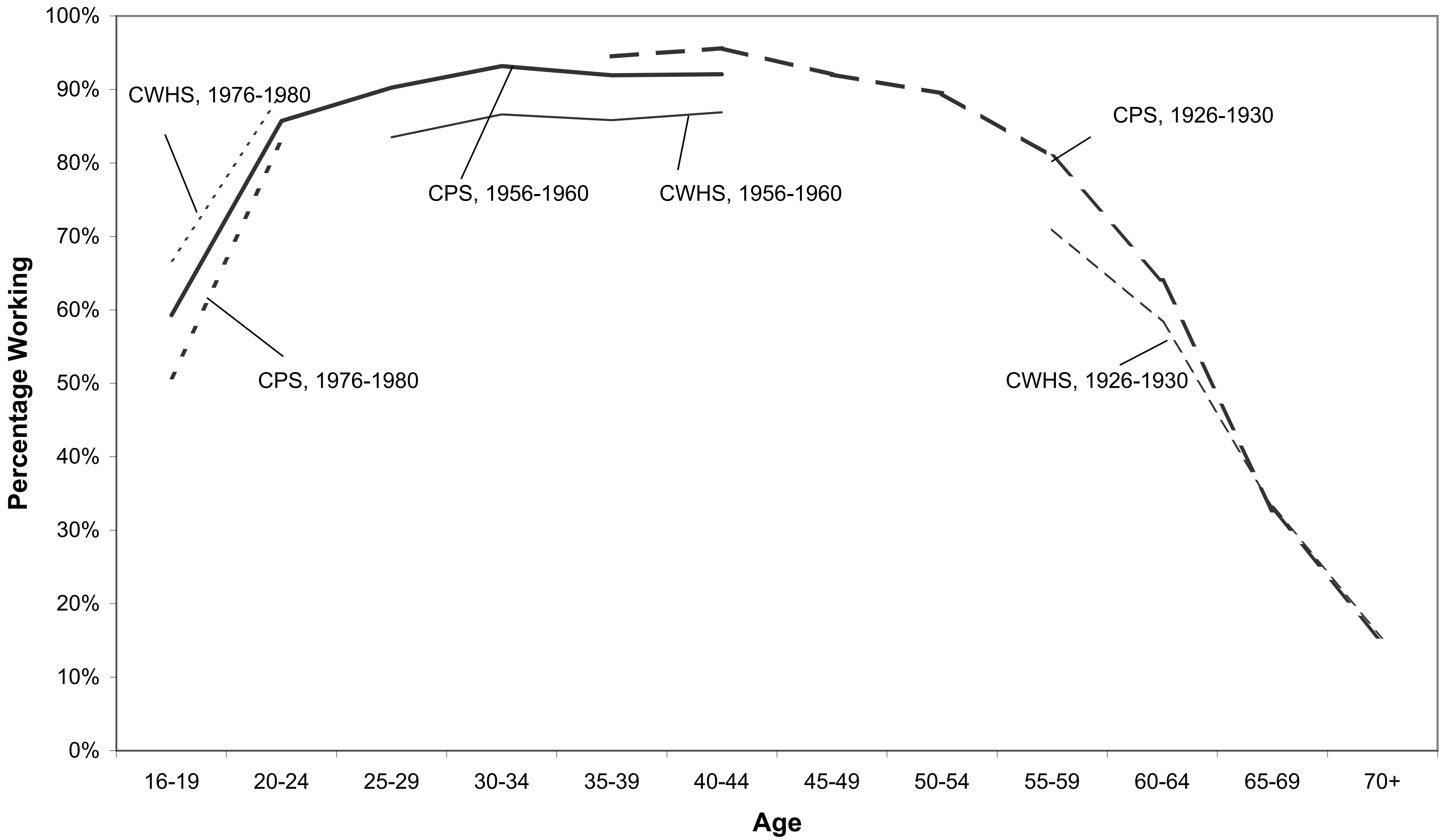

Figure 4. Female Cohort Labor Force Participation, CPS versus CWHS

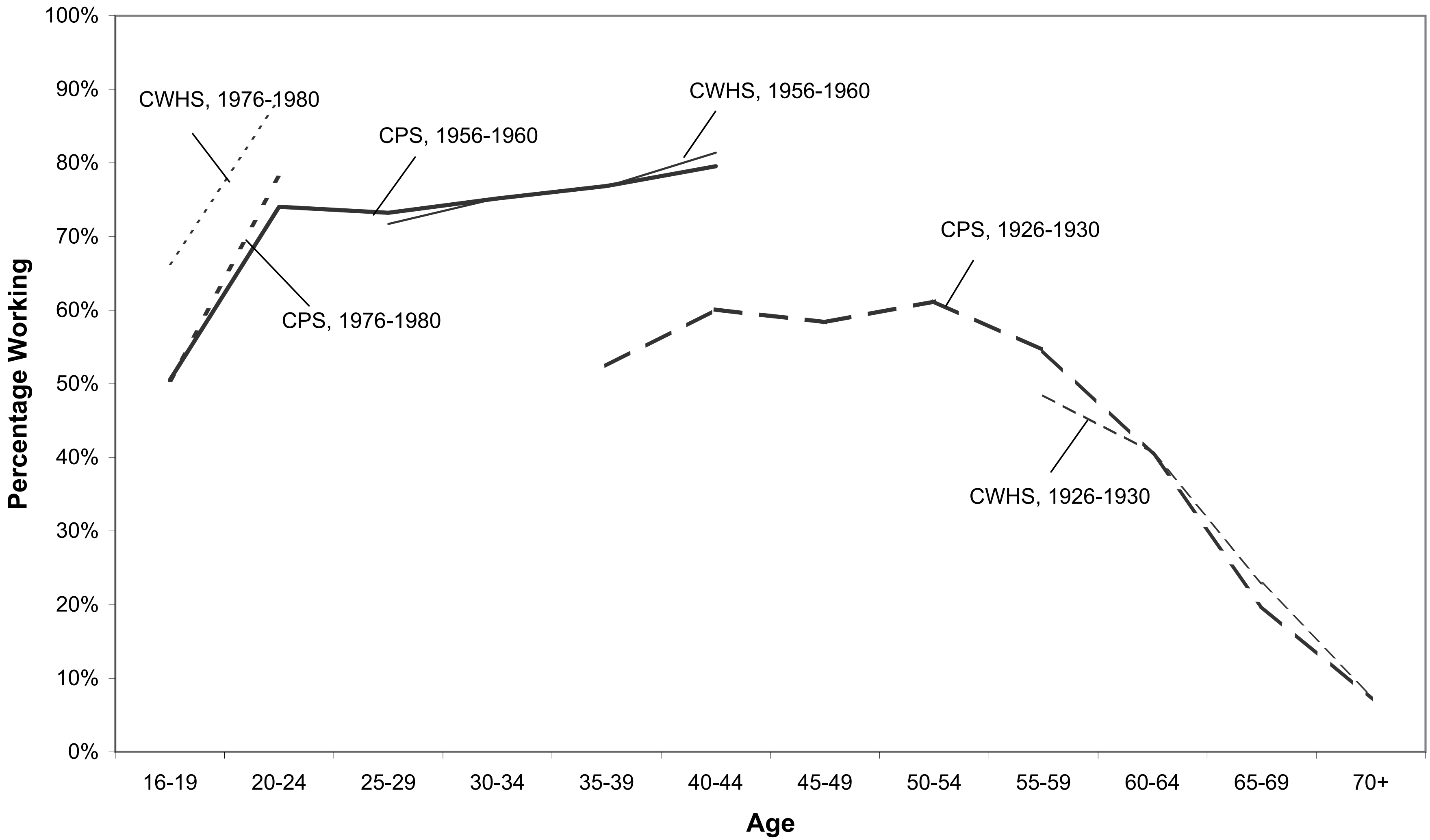

Table 1

Age-Centered Regression Coefficients, Male Labor Force Participation

Age Group	Age	OAI/DI	Never Mar	Married	Lag LFP	1910	1920	1930	1940	1950	1960	1970	1980	Constant	Time
16			0.0670	**1.6714**							**0.1207**	0.0066	0.0128	**-0.6218**	**-0.0078**
17	**0.3558**		**-0.1751**	**1.5254**	**1.9632**						**0.7882**	**0.6670**	**0.7242**	**-7.7871**	0.0005
18	**0.2597**		**-0.3537**	**0.8725**	**1.9694**						**0.4772**	**0.1965**	**0.1274**	**-6.0169**	**0.0191**
19	**0.1989**	**-0.3431**	**-0.5155**	**0.4680**	**2.0674**					**0.0379**	**0.4009**	0.0514	0.0514	**-4.8925**	**0.0257**
20	**0.1881**	**-0.4266**	**-0.5939**	**0.2500**	**2.2023**					**0.0830**	**0.3575**	-0.0133	-0.0133	**-4.7658**	**0.0296**
21	**0.1707**	**-0.5760**	**-0.6257**	**0.1438**	**2.3719**					**0.1279**	**0.2706**	**-0.1231**	-0.1231	**-4.5402**	**0.0342**
22	**0.1731**	**-0.7490**	**-0.6123**	**0.0670**	**2.5951**					**0.2001**	**0.2689**	-0.0899	-0.0899	**-4.7720**	**0.0331**
23	**0.1835**	**-0.9667**	**-0.5600**	0.0213	**2.8612**					**0.3145**	**0.3639**	0.0946	0.0946	**-5.2204**	**0.0258**
24	**0.1825**	**-1.1656**	**-0.4812**	0.0062	**3.1224**					**0.4615**	**0.5128**	**0.3611**	0.3611	**-5.4005**	**0.0146**
25	**0.1652**	**-1.3394**	**-0.3931**	0.0050	**3.3734**					**0.6266**	**0.6792**	**0.6552**	0.6552	**-5.1466**	0.0014
26	**0.1355**	**-1.4682**	**-0.3044**	0.0049	**3.6069**					**0.7512**	**0.7761**	**0.8457**	0.8457	**-4.5185**	**-0.0092**
27	**0.1075**	**-1.5890**	**-0.2202**	0.0189	**3.8002**					**0.7687**	**0.7015**	**0.8101**	0.8101	**-3.8994**	**-0.0116**
28	**0.0863**	**-1.6849**	**-0.1567**	0.0406	**3.9475**					**0.6972**	**0.5137**	**0.6075**	0.6075	**-3.4295**	**-0.0081**
29	**0.0496**	**-1.7839**	**-0.1220**	0.0527	**4.0633**				**-0.3815**	**0.1342**	**-0.2832**	-0.2832	-0.2832	**-2.2463**	**0.0099**
30	**0.0317**	**-1.8694**	**-0.1004**	**0.0627**	**4.1376**				**-0.2476**	**0.1294**	**-0.3609**	-0.3609	-0.3609	**-1.8867**	**0.0150**
31	**0.0187**	**-1.9342**	**-0.0955**	**0.0738**	**4.1984**				**-0.0804**	**0.1878**	**-0.3175**	-0.3175	-0.3175	**-1.6450**	**0.0164**
32	**0.0107**	**-1.9786**	**-0.1066**	**0.0836**	**4.2469**				**0.1364**	**0.3361**	-0.1103	-0.1103	-0.1103	**-1.5035**	**0.0116**
33	0.0076	**-2.0221**	**-0.1342**	**0.0808**	**4.3045**				**0.3885**	**0.5501**	**0.1901**	0.1901	0.1901	**-1.4866**	0.0030
34	**0.0079**	**-2.0390**	**-0.1707**	**0.0775**	**4.3649**				**0.6364**	**0.7649**	**0.4910**	0.4910	0.4910	**-1.5518**	**-0.0062**
35	**0.0145**	**-2.0529**	**-0.2082**	**0.0746**	**4.4297**				**0.8453**	**0.9442**	**0.7442**	0.7442	0.7442	**-1.8180**	**-0.0145**
36	**0.0219**	**-2.0848**	**-0.2413**	**0.0804**	**4.4813**				**0.9775**	**1.0142**	**0.8642**	0.8642	0.8642	**-2.1048**	**-0.0190**
37	**0.0301**	**-2.1426**	**-0.2742**	**0.0863**	**4.5170**				**1.0073**	**0.9631**	**0.8341**	0.8341	0.8341	**-2.4169**	**-0.0187**
38	**0.0350**	**-2.2122**	**-0.2934**	**0.1127**	**4.5203**				**0.9344**	**0.7917**	**0.6710**	0.6710	0.6710	**-2.5993**	**-0.0146**
39	**0.0258**	**-2.3146**	**-0.3182**	**0.1522**	**4.5160**			**-0.4264**	**0.3846**	0.0396	0.0396	0.0396	0.0396	**-1.9718**	-0.0010
40	**0.0205**	**-2.4109**	**-0.3376**	**0.2064**	**4.5019**			**-0.3347**	**0.3051**	-0.1193	-0.1193	-0.1193	-0.1193	**-1.8701**	**0.0065**
41	**0.0136**	**-2.4964**	**-0.3607**	**0.2556**	**4.5001**			**-0.2035**	**0.2935**	-0.1375	-0.1375	-0.1375	-0.1375	**-1.6930**	**0.0091**
42	0.0064	**-2.5726**	**-0.3908**	**0.3096**	**4.5050**			0.0028	**0.3993**	0.0253	0.0253	0.0253	0.0253	**-1.4949**	0.0058
43	0.0071	**-2.6421**	**-0.4332**	**0.3565**	**4.5403**			**0.2608**	**0.6192**	**0.3592**	0.3592	0.3592	0.3592	**-1.6206**	-0.0032
44	**0.0117**	**-2.7046**	**-0.4753**	**0.3889**	**4.5846**			**0.5216**	**0.8604**	**0.7149**	0.7149	0.7149	0.7149	**-1.8991**	**-0.0131**
45	**0.0127**	**-2.7528**	**-0.5038**	**0.4129**	**4.6286**			**0.7244**	**1.0293**	**0.9901**	0.9901	0.9901	0.9901	**-1.9971**	**-0.0207**
46	0.0082	**-2.8023**	**-0.5242**	**0.4355**	**4.6607**			**0.8619**	**1.0871**	**1.1055**	1.1055	1.1055	1.1055	**-1.8429**	**-0.0236**
47	-0.0081	**-2.8667**	**-0.5129**	**0.4582**	**4.6802**			**0.8933**	1.0239	**1.0622**	1.0622	1.0622	1.0622	**-1.1278**	**-0.0219**
48	**-0.0308**	**-2.9327**	**-0.4796**	**0.4877**	**4.6809**			**0.8388**	0.8632	**0.8842**	0.8842	0.8842	0.8842	-0.0908	**-0.0164**
49	**-0.0736**	**-3.0215**	**-0.4546**	**0.5093**	**4.6816**		**-0.4576**	**0.1957**	-0.0736	-0.0736	-0.0736	-0.0736	-0.0736	**2.2136**	**0.0065**
50	**-0.0833**	**-3.0894**	**-0.4380**	**0.5223**	**4.6666**		**-0.3463**	**0.2010**	-0.1310	-0.1310	-0.1310	-0.1310	-0.1310	**2.5939**	**0.0117**
51	**-0.0912**	**-3.1412**	**-0.4161**	**0.5345**	**4.6461**		**-0.2159**	**0.2118**	-0.1310	-0.1310	-0.1310	-0.1310	-0.1310	**2.9134**	**0.0143**
52	**-0.0909**	**-3.1669**	**-0.4095**	**0.5333**	**4.6306**		-0.0518	**0.2827**	-0.0166	-0.0166	-0.0166	-0.0166	-0.0166	**2.8369**	**0.0128**
53	**-0.0875**	**-3.1802**	**-0.4043**	**0.5190**	**4.6268**		**0.1595**	**0.4459**	**0.2399**	0.2399	0.2399	0.2399	0.2399	**2.6353**	0.0057

Table 1 (continued)

Age-Centered Regression Coefficients, Male Labor Force Participation

Age Group	Age	OAI/DI	Never Mar	Married	Lag LFP	1910	1920	1930	1940	1950	1960	1970	1980	Constant	Time
54	**-0.0851**	**-3.1717**	**-0.3817**	**0.5082**	**4.6339**		**0.3806**	**0.6452**	**0.5449**	0.5449	0.5449	0.5449	0.5449	**2.4949**	-0.0039
55	**-0.0829**	**-3.1471**	**-0.3549**	**0.4996**	**4.6548**		**0.5936**	**0.8471**	**0.8475**	0.8475	0.8475	0.8475	0.8475	**2.3762**	**-0.0144**
56	**-0.0873**	**-3.1254**	**-0.3309**	**0.4825**	**4.6922**		**0.7473**	**0.9943**	**1.0729**	1.0729	1.0729	1.0729	1.0729	**2.6236**	**-0.0223**
57	**-0.0997**	**-3.1036**	**-0.3124**	**0.4640**	**4.7207**		**0.7838**	**0.9911**	**1.0890**	1.0890	1.0890	1.0890	1.0890	**3.3255**	**-0.0237**
58	**-0.1148**	**-2.9719**	**-0.3171**	**0.4255**	**4.7171**		**0.7181**	**0.8700**	**0.9437**	0.9437	0.9437	0.9437	0.9437	**4.2095**	**-0.0197**
59	**-0.1343**	**-2.7301**	**-0.3176**	**0.3848**	**4.7030**	**-0.4290**	0.0446	-0.0752	-0.0752	-0.0752	-0.0752	-0.0752	-0.0752	**5.5521**	**0.0072**
60	**-0.1208**	**-2.5079**	**-0.3114**	**0.3361**	**4.6613**	**-0.3279**	-0.0182	**-0.1970**	-0.1970	-0.1970	-0.1970	-0.1970	-0.1970	**4.6553**	**0.0170**
61	**-0.0974**	**-2.2958**	**-0.2888**	**0.2855**	**4.5791**	**-0.2038**	-0.0201	**-0.2241**	-0.2241	-0.2241	-0.2241	-0.2241	-0.2241	**3.1664**	**0.0235**
62	**-0.0576**	**-2.1457**	**-0.2494**	**0.2469**	**4.4797**	-0.0233	**0.1063**	-0.0547	-0.0547	-0.0547	-0.0547	-0.0547	-0.0547	**0.6518**	**0.0239**
63	**-0.0166**	**-2.0409**	**-0.1900**	**0.2311**	**4.4265**	**0.1981**	**0.3196**	**0.2243**	0.2243	0.2243	0.2243	0.2243	0.2243	**-2.0237**	**0.0218**
64	**0.0101**	**-1.9247**	**-0.1318**	**0.2242**	**4.4190**	**0.4455**	**0.5930**	**0.5858**	0.5858	0.5858	0.5858	0.5858	0.5858	**-3.8842**	**0.0164**
65	**0.0224**	**-1.7897**	**-0.0882**	**0.2153**	**4.4517**	**0.7108**	**0.9032**	**0.9875**	0.9875	0.9875	0.9875	0.9875	0.9875	**-4.8811**	**0.0092**
66	**0.0248**	**-1.6834**	-0.0564	**0.2231**	**4.5589**	**0.9890**	**1.1932**	**1.3529**	1.3529	1.3529	1.3529	1.3529	1.3529	**-5.3005**	0.0034
67	**0.0090**	**-1.5771**	-0.0284	**0.2277**	**4.6944**	**1.1988**	**1.3552**	**1.5273**	1.5273	1.5273	1.5273	1.5273	1.5273	**-4.5539**	0.0034
68	-0.0012	**-1.4669**	-0.0150	**0.2198**	**4.8260**	**1.2996**	**1.3432**	**1.4528**	1.4528	1.4528	1.4528	1.4528	1.4528	**-4.1792**	**0.0098**
69	**-0.0156**	**-1.3720**	-0.0080	**0.2019**	**4.9534**	**1.2829**	**1.1659**	1.1659	1.1659	1.1659	1.1659	1.1659	1.1659	**-3.5052**	**0.0227**
70	**-0.0363**	**-1.2956**	0.0008	**0.1913**	**5.0766**	**1.1633**	**0.8506**	0.8506	0.8506	0.8506	0.8506	0.8506	0.8506	**-2.3703**	**0.0393**
71	**-0.0491**	**-1.1730**	0.0088	**0.1660**	**5.1646**	**0.8894**	**0.3752**	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752	**-1.7985**	**0.0613**
72	**-0.0654**	**-1.0233**	0.0040	**0.1363**	**5.2469**	**0.5707**	-0.1127	-0.1127	-0.1127	-0.1127	-0.1127	-0.1127	-0.1127	**-0.9751**	**0.0830**
73	**-0.0841**	**-0.8454**	-0.0043	**0.1101**	**5.3256**	**0.2522**	**-0.5667**	-0.5667	-0.5667	-0.5667	-0.5667	-0.5667	-0.5667	0.0265	**0.1025**
74	**-0.0998**	**-0.6799**	-0.0062	**0.0972**	**5.4082**	-0.0509	**-0.9747**	-0.9747	-0.9747	-0.9747	-0.9747	-0.9747	-0.9747	**0.8380**	**0.1193**
75	**-0.1139**	**-0.5361**	-0.0010	**0.0892**	**5.4943**	**-0.3202**	**-1.3227**	-1.3227	-1.3227	-1.3227	-1.3227	-1.3227	-1.3227	**1.5858**	**0.1330**
76	**-0.1236**	**-0.4347**	0.0002	**0.0875**	**5.5719**	**-0.5704**	**-1.6333**	-1.6333	-1.6333	-1.6333	-1.6333	-1.6333	-1.6333	**2.0660**	**0.1444**
77	**-0.1250**	**-0.3800**	0.0088	**0.0908**	**5.6494**	**-0.7578**	**-1.8519**	-1.8519	-1.8519	-1.8519	-1.8519	-1.8519	-1.8519	**1.9948**	**0.1523**
78	**-0.1287**	**-0.3818**	0.0077	**0.0921**	**5.7276**	**-0.9082**	**-2.0028**	-2.0028	-2.0028	-2.0028	-2.0028	-2.0028	-2.0028	**2.1648**	**0.1582**
79	**-0.1149**	**-0.3566**	-0.0090	**0.0976**	**5.8373**	**-1.0453**	-1.0453	-1.0453	-1.0453	-1.0453	-1.0453	-1.0453	-1.0453	**1.0339**	**0.1505**
80	**-0.1146**	**-0.3769**	-0.0518	**0.1025**	**5.9030**	**-1.1285**	-1.1285	-1.1285	-1.1285	-1.1285	-1.1285	-1.1285	-1.1285	0.9043	**0.1562**
81	**-0.1166**	**-0.3880**	-0.0861	**0.1150**	**5.9734**	**-1.1514**	-1.1514	-1.1514	-1.1514	-1.1514	-1.1514	-1.1514	-1.1514	0.9703	**0.1591**
82	**-0.1157**	**-0.4167**	-0.1054	**0.1310**	**6.0693**	**-1.1685**	-1.1685	-1.1685	-1.1685	-1.1685	-1.1685	-1.1685	-1.1685	0.7732	**0.1627**
83	**-0.1272**	**-0.4320**	-0.0875	**0.1589**	**6.1528**	**-1.1646**	-1.1646	-1.1646	-1.1646	-1.1646	-1.1646	-1.1646	-1.1646	1.6055	**0.1640**
84	**-0.1252**	**-0.4143**	-0.0376	**0.1868**	**6.2265**	**-1.1483**	-1.1483	-1.1483	-1.1483	-1.1483	-1.1483	-1.1483	-1.1483	1.3469	**0.1641**
85	**-0.1142**	**-0.3988**	0.0619	**0.1871**	**6.3162**	**-1.1331**	-1.1331	-1.1331	-1.1331	-1.1331	-1.1331	-1.1331	-1.1331	0.3017	**0.1656**
86	**-0.0892**	**-0.4599**	0.1996	**0.1764**	**6.4760**	**-1.1383**	-1.1383	-1.1383	-1.1383	-1.1383	-1.1383	-1.1383	-1.1383	-1.9628	**0.1698**
87	**-0.0622**	**-0.4761**	0.3200	**0.1948**	**6.5484**	**-1.0704**	-1.0704	-1.0704	-1.0704	-1.0704	-1.0704	-1.0704	-1.0704	**-4.3740**	**0.1692**
88	0.0379	**-0.6325**	0.2345	0.2353	**6.8503**	**-0.8848**	-0.8848	-0.8848	-0.8848	-0.8848	-0.8848	-0.8848	-0.8848	**-13.3847**	**0.1742**
89	-0.1393	**-0.8305**	0.5303	0.1392	**7.9466**	-0.7732	-0.7732	-0.7732	-0.7732	-0.7732	-0.7732	-0.7732	-0.7732	1.2112	**0.2005**
90		**-1.8214**	1.2545	0.2426	**7.9211**									**-10.0794**	**0.1682**

Bold indicates statistical significance at the 10% level.

Table 2

Age-Centered Regression Coefficients, Female Labor Force Participation

Age Group	Age	OAI/DI	Never Mar	Married	Lag LFP	1910	1920	1930	1940	1950	1960	1970	1980	Constant	Time
16			-0.0954	**-0.4605**							**0.1934**	0.0386	-0.0560	**-1.0257**	**0.0111**
17	**0.3558**		0.0106	**-0.3664**	**2.1133**						**1.0008**	**0.8085**	**0.8026**	**-8.5719**	**0.0152**
18	**0.2570**		0.0374	**-0.3332**	**2.0688**						**0.5964**	**0.2935**	**0.2293**	**-6.7872**	**0.0272**
19	**0.1847**	**-0.2671**	**0.0456**	**-0.3613**	**2.1842**					**-0.2435**	**0.1250**	**-0.3813**	-0.3813	**-5.4212**	**0.0435**
20	**0.1602**	**-0.3329**	**0.0937**	**-0.4019**	**2.3370**					**-0.0732**	**0.1789**	**-0.3629**	-0.3629	**-5.2621**	**0.0478**
21	**0.1278**	**-0.4395**	**0.1251**	**-0.4378**	**2.5020**					**0.0764**	**0.1802**	**-0.3991**	-0.3991	**-4.8562**	**0.0525**
22	**0.1058**	**-0.5594**	**0.1795**	**-0.4782**	**2.6956**					**0.2817**	**0.3011**	**-0.2501**	-0.2501	**-4.6678**	**0.0517**
23	**0.0849**	**-0.6855**	**0.2328**	**-0.5300**	**2.9142**					**0.5237**	**0.5055**	0.0178	0.0178	**-4.4866**	**0.0478**
24	**0.0631**	**-0.7745**	**0.2882**	**-0.5828**	**3.1198**					**0.7623**	**0.7147**	**0.2972**	0.2972	**-4.2302**	**0.0436**
25	**0.0436**	**-0.8347**	**0.3339**	**-0.6418**	**3.3089**					**0.9703**	**0.8692**	**0.5135**	0.5135	**-3.9600**	**0.0411**
26	**0.0293**	**-0.8491**	**0.3623**	**-0.6981**	**3.4631**					**1.1084**	**0.9248**	**0.6077**	0.6077	**-3.7570**	**0.0420**
27	**0.0232**	**-0.8755**	**0.3445**	**-0.7510**	**3.5756**					**1.1125**	**0.8007**	**0.4623**	0.4623	**-3.7220**	**0.0499**
28	**0.0210**	**-0.8956**	**0.3029**	**-0.7917**	**3.6463**					**1.0030**	**0.5392**	**0.1500**	0.1500	**-3.7611**	**0.0620**
29	**0.0154**	**-0.8973**	**0.2389**	**-0.8272**	**3.7015**				**-0.2399**	**0.6397**	-0.0427	-0.0427	-0.0427	**-3.4810**	**0.0746**
30	**0.0150**	**-0.8859**	**0.1944**	**-0.8395**	**3.7378**				**-0.1413**	**0.5125**	**-0.2899**	-0.2899	-0.2899	**-3.6284**	**0.0874**
31	**0.0161**	**-0.8931**	**0.1609**	**-0.8402**	**3.7793**				**-0.0031**	**0.4360**	**-0.4206**	-0.4206	-0.4206	**-3.8126**	**0.0951**
32	**0.0239**	**-0.8829**	**0.1375**	**-0.8315**	**3.8189**				**0.2201**	**0.5109**	**-0.2971**	-0.2971	-0.2971	**-4.1752**	**0.0928**
33	0.0375	**-0.8705**	**0.1177**	**-0.8184**	**3.8739**				**0.5086**	**0.7269**	0.0483	0.0483	0.0483	**-4.7001**	**0.0814**
34	**0.0518**	**-0.8600**	**0.1014**	**-0.8081**	**3.9428**				**0.8350**	**1.0260**	**0.5169**	0.5169	0.5169	**-5.2230**	**0.0651**
35	**0.0622**	**-0.8519**	**0.0887**	**-0.8008**	**4.0298**				**1.1584**	**1.3226**	**0.9708**	0.9708	0.9708	**-5.6189**	**0.0488**
36	**0.0665**	**-0.8439**	**0.0715**	**-0.7988**	**4.1210**				**1.4079**	**1.5181**	**1.2764**	1.2764	1.2764	**-5.8113**	**0.0375**
37	**0.0609**	**-0.8472**	**0.0564**	**-0.7962**	**4.2059**				**1.4847**	**1.4753**	**1.2528**	1.2528	1.2528	**-5.6743**	**0.0372**
38	**0.0487**	**-0.8593**	**0.0513**	**-0.7922**	**4.2685**				**1.4065**	**1.2371**	**0.9736**	0.9736	0.9736	**-5.3005**	**0.0454**
39	**0.0211**	**-0.8767**	0.0341	**-0.7876**	**4.3245**			**-0.3850**	**0.8256**	**0.3093**	0.3093	0.3093	0.3093	**-4.0961**	**0.0674**
40	**0.0095**	**-0.8963**	0.0265	**-0.7845**	**4.3555**			**-0.2964**	**0.6426**	-0.0382	-0.0382	-0.0382	-0.0382	**-3.8135**	**0.0833**
41	0.0024	**-0.9057**	0.0132	**-0.7831**	**4.3795**			**-0.1707**	**0.5097**	**-0.2526**	-0.2526	-0.2526	-0.2526	**-3.6692**	**0.0936**
42	0.0033	**-0.9198**	-0.0004	**-0.7858**	**4.3954**			**0.0458**	**0.5605**	**-0.1523**	-0.1523	-0.1523	-0.1523	**-3.7948**	**0.0921**
43	**0.0112**	**-0.9302**	-0.0260	**-0.7913**	**4.4177**			**0.3473**	**0.7897**	**0.2227**	0.2227	0.2227	0.2227	**-4.1697**	**0.0800**
44	**0.0230**	**-0.9400**	-0.0428	**-0.7988**	**4.4622**			**0.7040**	**1.1191**	**0.7544**	0.7544	0.7544	0.7544	**-4.6922**	**0.0620**
45	**0.0329**	**-0.9452**	**-0.0505**	**-0.8102**	**4.5324**			**1.0841**	**1.4857**	**1.3134**	1.3134	1.3134	1.3134	**-5.1357**	**0.0424**
46	**0.0357**	**-0.9554**	-0.0409	**-0.8198**	**4.6210**			**1.3844**	**1.7288**	**1.6879**	1.6879	1.6879	1.6879	**-5.2894**	**0.0291**
47	**0.0292**	**-0.9604**	-0.0292	**-0.8319**	**4.7081**			**1.5086**	**1.7192**	**1.7079**	1.7079	1.7079	1.7079	**-5.0545**	**0.0275**
48	**0.0182**	**-0.9784**	0.0001	**-0.8442**	**4.7721**			**1.4655**	**1.4847**	**1.4353**	1.4353	1.4353	1.4353	**-4.6202**	**0.0356**
49	**-0.0323**	**-0.9955**	0.0084	**-0.8495**	**4.8309**		**-0.5684**	**0.5548**	0.0280	0.0280	0.0280	0.0280	0.0280	**-1.9958**	**0.0752**
50	**-0.0452**	**-1.0287**	0.0394	**-0.8544**	**4.8571**		**-0.4800**	**0.3660**	**-0.3532**	-0.3532	-0.3532	-0.3532	-0.3532	**-1.5342**	**0.0922**
51	**-0.0517**	**-1.0697**	**0.0592**	**-0.8660**	**4.8681**		**-0.3436**	**0.2534**	**-0.5518**	-0.5518	-0.5518	-0.5518	-0.5518	**-1.3402**	**0.1020**
52	**-0.0464**	**-1.1269**	**0.0853**	**-0.8776**	**4.8657**		**-0.1052**	**0.3415**	**-0.3985**	-0.3985	-0.3985	-0.3985	-0.3985	**-1.6863**	**0.0983**
53	**-0.0359**	**-1.1740**	**0.1033**	**-0.8910**	**4.8678**		**0.2246**	**0.5966**	0.0300	0.0300	0.0300	0.0300	0.0300	**-2.2555**	**0.0840**

Table 2 (continued)

Age	Age-Centered Regression Coefficients, Female Labor Force Participation														
Group	Age	OAI/DI	Never Mar	Married	Lag LFP	1910	1920	1930	1940	1950	1960	1970	1980	Constant	Time
54	**-0.0246**	**-1.2168**	**0.1228**	**-0.9046**	**4.8923**		**0.6109**	**0.9423**	**0.5969**	0.5969	0.5969	0.5969	0.5969	**-2.8485**	**0.0640**
55	**-0.0143**	**-1.2439**	**0.1346**	**-0.9157**	**4.9443**		**1.0289**	**1.3458**	**1.2191**	1.2191	1.2191	1.2191	1.2191	**-3.3962**	**0.0416**
56	**-0.0127**	**-1.2799**	**0.1620**	**-0.9200**	**5.0160**		**1.3881**	**1.6419**	**1.6716**	1.6716	1.6716	1.6716	1.6716	**-3.4900**	**0.0247**
57	**-0.0204**	**-1.3134**	**0.1827**	**-0.9250**	**5.0826**		**1.5594**	**1.6783**	**1.7447**	1.7447	1.7447	1.7447	1.7447	**-3.1004**	**0.0204**
58	**-0.0350**	**-1.3623**	**0.1946**	**-0.9253**	**5.1277**		**1.5329**	**1.4691**	**1.5008**	1.5008	1.5008	1.5008	1.5008	**-2.3296**	**0.0269**
59	**-0.0842**	**-1.3578**	**0.1873**	**-0.9146**	**5.1566**	**-0.5648**	**0.6053**	0.0383	0.0383	0.0383	0.0383	0.0383	0.0383	**0.7418**	**0.0663**
60	**-0.0898**	**-1.3323**	**0.1890**	**-0.9044**	**5.1447**	**-0.4589**	**0.4217**	**-0.3350**	-0.3350	-0.3350	-0.3350	-0.3350	-0.3350	**0.9037**	**0.0836**
61	**-0.0923**	**-1.2844**	**0.1700**	**-0.8861**	**5.1110**	**-0.3348**	**0.2305**	**-0.6400**	-0.6400	-0.6400	-0.6400	-0.6400	-0.6400	**0.9030**	**0.0984**
62	**-0.0872**	**-1.2292**	**0.1575**	**-0.8572**	**5.0700**	**-0.1336**	**0.1991**	**-0.6759**	-0.6759	-0.6759	-0.6759	-0.6759	-0.6759	**0.4506**	**0.1036**
63	**-0.0748**	**-1.1615**	**0.1551**	**-0.8269**	**5.0361**	**0.1466**	**0.3449**	**-0.4355**	-0.4355	-0.4355	-0.4355	-0.4355	-0.4355	-0.4318	**0.0995**
64	**-0.0633**	**-1.0817**	**0.1538**	**-0.7950**	**5.0292**	**0.4859**	**0.6164**	-0.0112	-0.0112	-0.0112	-0.0112	-0.0112	-0.0112	**-1.2846**	**0.0890**
65	**-0.0530**	**-0.9821**	**0.1621**	**-0.7600**	**5.0423**	**0.8878**	**0.9930**	**0.5605**	0.5605	0.5605	0.5605	0.5605	0.5605	**-2.0711**	**0.0731**
66	**-0.0456**	**-0.8704**	**0.1899**	**-0.7338**	**5.1084**	**1.3435**	**1.4604**	**1.2311**	1.2311	1.2311	1.2311	1.2311	1.2311	**-2.6998**	**0.0537**
67	**-0.0493**	**-0.7401**	**0.2284**	**-0.7113**	**5.2235**	**1.7428**	**1.8433**	**1.7596**	1.7596	1.7596	1.7596	1.7596	1.7596	**-2.6626**	**0.0393**
68	**-0.0545**	**-0.5908**	**0.2737**	**-0.6831**	**5.3494**	**2.0030**	**2.0137**	**1.9776**	1.9776	1.9776	1.9776	1.9776	1.9776	**-2.5819**	**0.0344**
69	**-0.0644**	**-0.4350**	**0.3330**	**-0.6544**	**5.4774**	**2.0894**	**1.9366**	1.9366	1.9366	1.9366	1.9366	1.9366	1.9366	**-2.2295**	**0.0394**
70	**-0.0848**	**-0.2878**	**0.3856**	**-0.6284**	**5.6131**	**1.9385**	**1.5648**	1.5648	1.5648	1.5648	1.5648	1.5648	1.5648	**-1.1968**	**0.0570**
71	**-0.1037**	-0.1512	**0.4398**	**-0.5933**	**5.7417**	**1.5345**	0.8664	0.8664	0.8664	0.8664	0.8664	0.8664	0.8664	-0.3159	**0.0874**
72	**-0.1202**	**-0.0162**	**0.4815**	**-0.5518**	**5.8511**	**1.0714**	**0.1388**	0.1388	0.1388	0.1388	0.1388	0.1388	0.1388	0.4235	**0.1177**
73	**-0.1355**	**0.0916**	**0.5140**	**-0.5250**	**5.9643**	**0.6214**	**-0.5458**	-0.5458	-0.5458	-0.5458	-0.5458	-0.5458	-0.5458	**1.1262**	**0.1459**
74	**-0.1472**	**0.1723**	**0.5446**	**-0.5032**	**6.0863**	**0.1910**	**-1.1453**	-1.1453	-1.1453	-1.1453	-1.1453	-1.1453	-1.1453	**1.5991**	**0.1712**
75	**-0.1568**	**0.2127**	**0.5806**	**-0.4879**	**6.2144**	**-0.2048**	**-1.6617**	-1.6617	-1.6617	-1.6617	-1.6617	-1.6617	-1.6617	**1.9822**	**0.1929**
76	**-0.1579**	**0.2318**	**0.6006**	**-0.4874**	**6.3328**	**-0.5565**	**-2.0527**	-2.0527	-2.0527	-2.0527	-2.0527	-2.0527	-2.0527	**1.8165**	**0.2092**
77	**-0.1611**	**0.2207**	**0.6328**	**-0.5036**	**6.4799**	**-0.8452**	**-2.3552**	-2.3552	-2.3552	-2.3552	-2.3552	-2.3552	-2.3552	**1.8203**	**0.2227**
78	**-0.1676**	**0.2315**	**0.6794**	**-0.4901**	**6.6289**	**-1.0726**	**-2.4841**	-2.4841	-2.4841	-2.4841	-2.4841	-2.4841	-2.4841	**2.1019**	**0.2311**
79	**-0.1536**	**0.2340**	**0.7061**	**-0.5027**	**6.8523**	**-1.2206**	-1.2206	-1.2206	-1.2206	-1.2206	-1.2206	-1.2206	-1.2206	0.9343	**0.2183**
80	**-0.1674**	**0.2123**	**0.7346**	**-0.5089**	**6.9214**	**-1.4192**	-1.4192	-1.4192	-1.4192	-1.4192	-1.4192	-1.4192	-1.4192	**1.8840**	**0.2282**
81	**-0.1697**	**0.2186**	**0.7635**	**-0.4798**	**6.9235**	**-1.5631**	-1.5631	-1.5631	-1.5631	-1.5631	-1.5631	-1.5631	-1.5631	**1.9829**	**0.2348**
82	**-0.1727**	**0.2159**	**0.7773**	**-0.4133**	**6.8575**	**-1.6555**	-1.6555	-1.6555	-1.6555	-1.6555	-1.6555	-1.6555	-1.6555	**2.2648**	**0.2368**
83	**-0.1676**	0.1462	**0.7682**	**-0.3845**	**6.7630**	**-1.7207**	-1.7207	-1.7207	-1.7207	-1.7207	-1.7207	-1.7207	-1.7207	**2.0138**	**0.2366**
84	**-0.1646**	0.0810	**0.7606**	**-0.3262**	**6.7186**	**-1.7816**	-1.7816	-1.7816	-1.7816	-1.7816	-1.7816	-1.7816	-1.7816	1.8604	**0.2370**
85	**-0.1683**	-0.0192	**0.7156**	**-0.2487**	**6.7171**	**-1.8493**	-1.8493	-1.8493	-1.8493	-1.8493	-1.8493	-1.8493	-1.8493	2.2348	**0.2385**
86	**-0.1731**	-0.1932	**0.6266**	-0.1199	**6.8677**	**-1.8383**	-1.8383	-1.8383	-1.8383	-1.8383	-1.8383	-1.8383	-1.8383	2.6100	**0.2406**
87	**-0.1761**	-0.3885	**0.4051**	0.0345	**7.1895**	**-1.8560**	-1.8560	-1.8560	-1.8560	-1.8560	-1.8560	-1.8560	-1.8560	2.6506	**0.2479**
88	**-0.1469**	-0.3475	0.1143	0.4443	**7.6419**	**-1.3854**	-1.3854	-1.3854	-1.3854	-1.3854	-1.3854	-1.3854	-1.3854	-0.3821	**0.2461**
89	**-0.1493**	**-0.5246**	**0.5186**	**0.8816**	**7.4674**	**-0.8098**	-0.8098	-0.8098	-0.8098	-0.8098	-0.8098	-0.8098	-0.8098	0.3375	**0.2260**
90		**-0.9363**	**1.1464**	**1.1705**	**7.4942**									**-13.1995**	**0.2309**

Bold indicates statistical significance at the 10% level.

Figure 5. Male Cohort Full-Time Employment, PSID 1968-1992

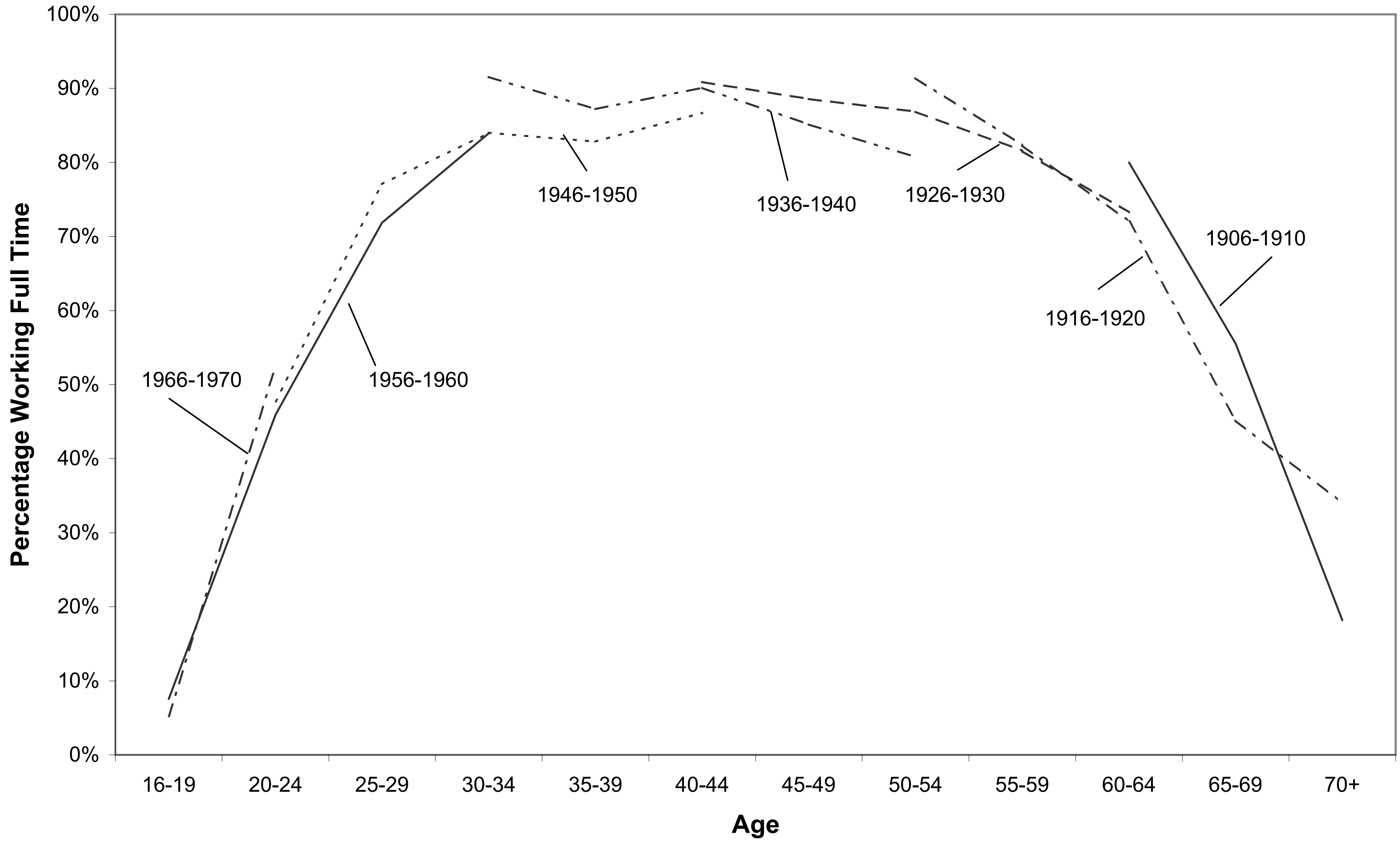

Figure 6. Female Cohort Full-Time Employment, PSID 1968-1992

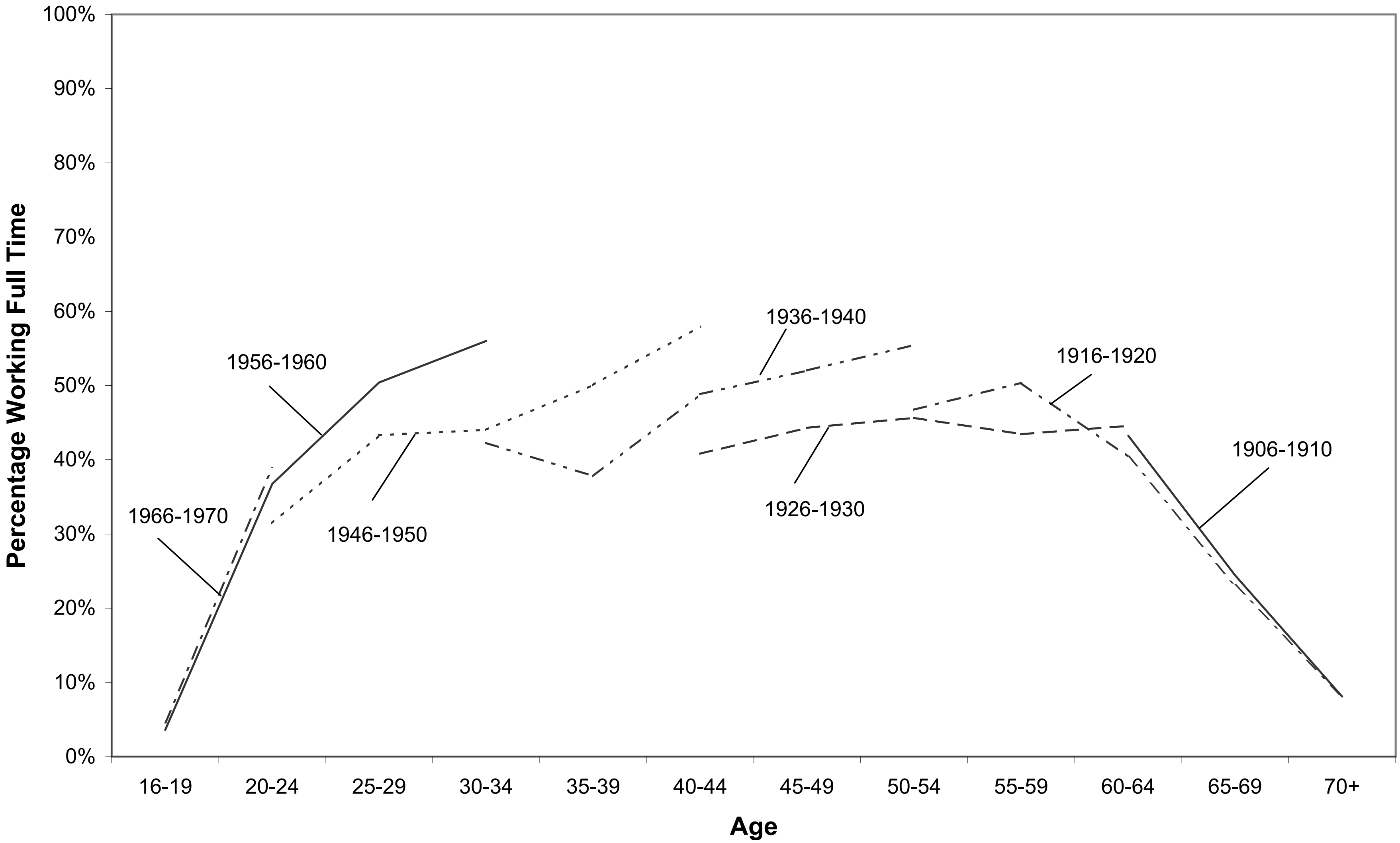

Table 3

Age Group	Age	Never Mar	Married	Lag LFP	Lag FT	1910	1920	1930	1940	1950	1960	1970	Constant
	Age-Centered Regression Coefficients, Male Full-Time Employment												
16											-0.3984	-0.1248	**-4.9628**
17	**0.7096**	-1.5936	0.7383	0.2548	**2.6291**						**-0.6641**	**-0.6390**	**-14.6648**
18	**0.8661**	**-0.7407**	**1.1593**	**0.5797**	**2.0440**						**-0.1981**	-0.0926	**-18.6692**
19	**0.5362**	**-0.4174**	**1.0730**	**0.5095**	**2.0085**						-0.0484	-0.0291	**-12.6357**
20	**0.3409**	**-0.4267**	**0.7884**	**0.4303**	**2.0551**						0.0112	-0.0254	**-8.6449**
21	**0.2656**	**-0.3605**	**0.7209**	**0.3498**	**2.0858**					-0.0172	0.0291	0.0291	**-7.0347**
22	**0.1971**	**-0.3202**	**0.6494**	**0.2709**	**2.0977**					-0.0949	-0.0086	-0.0086	**-5.4388**
23	**0.1423**	**-0.2492**	**0.6259**	**0.2089**	**2.0917**					**-0.1483**	-0.0240	-0.0240	**-4.1481**
24	**0.1064**	**-0.1847**	**0.6060**	**0.2088**	**2.0654**					**-0.1925**	-0.0307	-0.0307	**-3.2905**
25	**0.0842**	**-0.1228**	**0.5972**	**0.2455**	**2.0566**					**-0.2145**	-0.0254	-0.0254	**-2.7964**
26	**0.0711**	-0.0814	**0.5964**	**0.2975**	**2.0432**					**-0.2154**	-0.0090	-0.0090	**-2.5331**
27	**0.0562**	-0.0475	**0.6010**	**0.3594**	**2.0421**					**-0.2137**	-0.0026	-0.0026	**-2.2140**
28	**0.0430**	-0.0620	**0.5935**	**0.4028**	**2.0513**					**-0.2032**	0.0048	0.0048	**-1.8934**
29	**0.0351**	-0.0918	**0.5871**	**0.3727**	**2.0868**					**-0.1909**	-0.0030	-0.0030	**-1.6534**
30	**0.0260**	**-0.1347**	**0.5777**	**0.3232**	**2.1288**					**-0.1758**	-0.0236	-0.0236	**-1.3477**
31	0.0087	**-0.1818**	**0.5627**	**0.2993**	**2.1796**				**-0.3713**	**-0.4857**	-0.4857	-0.4857	**-0.4603**
32	0.0050	**-0.2498**	**0.5490**	**0.2984**	**2.2208**				**-0.3026**	**-0.3952**	-0.3952	-0.3952	-0.4252
33	0.0078	**-0.2749**	**0.5477**	**0.3233**	**2.2671**				**-0.3155**	**-0.3707**	-0.3707	-0.3707	**-0.5749**
34	0.0070	**-0.2926**	**0.5495**	**0.3796**	**2.3046**				**-0.3120**	**-0.3199**	-0.3199	-0.3199	**-0.6570**
35	0.0071	**-0.3256**	**0.5265**	**0.4675**	**2.3276**				**-0.2713**	**-0.2518**	-0.2518	-0.2518	**-0.7927**
36	0.0008	**-0.3413**	**0.5004**	**0.5304**	**2.3416**				**-0.2619**	**-0.2195**	-0.2195	-0.2195	**-0.6418**
37	0.0013	**-0.3378**	**0.4803**	**0.5406**	**2.3677**				**-0.2568**	**-0.2184**	-0.2184	-0.2184	-0.6685
38	0.0011	**-0.3577**	**0.4438**	**0.5103**	**2.3902**				**-0.2208**	**-0.2182**	-0.2182	-0.2182	-0.6323
39	-0.0006	**-0.3594**	**0.4081**	**0.4831**	**2.4180**				**-0.1781**	**-0.2308**	-0.2308	-0.2308	-0.5462
40	-0.0037	**-0.3198**	**0.4195**	**0.4176**	**2.4608**				**-0.1553**	**-0.2579**	-0.2579	-0.2579	-0.4049
41	-0.0082	**-0.2805**	**0.4041**	**0.3366**	**2.4939**			**-0.2546**	**-0.3841**	-0.3841	-0.3841	-0.3841	0.0433
42	-0.0162	-0.2296	**0.3897**	**0.2757**	**2.5169**			**-0.2623**	**-0.3530**	-0.3530	-0.3530	-0.3530	0.3989
43	-0.0180	-0.1467	**0.3875**	0.2314	**2.5231**			**-0.2344**	**-0.2781**	-0.2781	-0.2781	-0.2781	0.4602
44	-0.0168	-0.1150	**0.3802**	0.1880	**2.5067**			**-0.2150**	**-0.2218**	-0.2218	-0.2218	-0.2218	0.4265
45	-0.0154	-0.0803	**0.3374**	0.1536	**2.4691**			**-0.2253**	**-0.2011**	-0.2011	-0.2011	-0.2011	0.4453
46	-0.0127	-0.1187	**0.3144**	0.1660	**2.4551**			**-0.2060**	**-0.1573**	-0.1573	-0.1573	-0.1573	0.3109
47	**-0.0240**	-0.1623	**0.2841**	0.1826	**2.4401**			**-0.1647**	-0.1176	-0.1176	-0.1176	-0.1176	0.8231

Table 3 (continued)

Age-Centered Regression Coefficients, Male Full-Time Employment

Age Group	Age	Never Mar	Married	Lag LFP	Lag FT	1910	1920	1930	1940	1950	1960	1970	Constant
48	**-0.0405**	-0.2877	**0.2385**	0.1843	**2.4285**			**-0.1552**	-0.1300	-0.1300	-0.1300	-0.1300	**1.6543**
49	**-0.0492**	-0.3671	**0.1985**	0.1930	**2.4352**			**-0.1381**	**-0.1485**	-0.1485	-0.1485	-0.1485	**2.0973**
50	**-0.0528**	**-0.4163**	**0.1863**	0.2042	**2.4598**			-0.1054	-0.1399	-0.1399	-0.1399	-0.1399	**2.2533**
51	**-0.0484**	**-0.4294**	**0.2111**	0.2115	**2.4461**		-0.1943	**-0.2686**	-0.2686	-0.2686	-0.2686	-0.2686	**2.1749**
52	**-0.0363**	**-0.4043**	**0.2709**	0.2309	**2.4484**		-0.1472	-0.2040	-0.2040	-0.2040	-0.2040	-0.2040	**1.4220**
53	**-0.0376**	-0.2865	**0.3605**	0.2203	**2.4912**		-0.1442	-0.1604	-0.1604	-0.1604	-0.1604	-0.1604	**1.3657**
54	**-0.0416**	-0.2197	**0.4282**	0.2022	**2.5199**		-0.1291	-0.1092	-0.1092	-0.1092	-0.1092	-0.1092	**1.4868**
55	**-0.0491**	-0.1850	**0.5013**	0.1997	**2.5260**		-0.1053	-0.0471	-0.0471	-0.0471	-0.0471	-0.0471	**1.7973**
56	**-0.0522**	-0.0582	**0.5718**	0.1850	**2.5650**		-0.1029	-0.0068	-0.0068	-0.0068	-0.0068	-0.0068	**1.8799**
57	**-0.0488**	0.0597	**0.6015**	0.1894	**2.5819**		-0.0732	0.0274	0.0274	0.0274	0.0274	0.0274	**1.6213**
58	**-0.0538**	0.0989	**0.5958**	0.2370	**2.5653**		-0.0314	0.0582	0.0582	0.0582	0.0582	0.0582	**1.8462**
59	**-0.0723**	0.1305	**0.5948**	0.2745	**2.5533**		-0.0223	0.0503	0.0503	0.0503	0.0503	0.0503	**2.8883**
60	**-0.1099**	0.1429	**0.5568**	0.3029	**2.5496**		-0.0379	-0.0150	-0.0150	-0.0150	-0.0150	-0.0150	**5.1498**
61	**-0.1539**	0.0040	**0.4544**	0.3268	**2.5256**	**-0.5902**	**-0.5862**	-0.5862	-0.5862	-0.5862	-0.5862	-0.5862	**8.4470**
62	**-0.1925**	-0.1648	**0.3443**	0.2651	**2.5124**	**-0.4953**	**-0.5069**	-0.5069	-0.5069	-0.5069	-0.5069	-0.5069	**10.9039**
63	**-0.2271**	-0.2941	**0.2570**	0.1773	**2.4844**	**-0.4270**	**-0.4716**	-0.4716	-0.4716	-0.4716	-0.4716	-0.4716	**13.2013**
64	**-0.2471**	-0.3743	0.1780	0.0467	**2.4756**	**-0.3471**	**-0.4146**	-0.4146	-0.4146	-0.4146	-0.4146	-0.4146	**14.6193**
65	**-0.2324**	-0.4410	0.1461	-0.0467	**2.4834**	-0.2046	**-0.2799**	-0.2799	-0.2799	-0.2799	-0.2799	-0.2799	**13.6884**
66	**-0.1994**	-0.3742	0.1906	-0.1377	**2.4853**	-0.0452	-0.1155	-0.1155	-0.1155	-0.1155	-0.1155	-0.1155	**11.4459**
67	**-0.1530**	-0.2056	**0.2889**	-0.1377	**2.5487**	0.0665	0.0127	0.0127	0.0127	0.0127	0.0127	0.0127	**8.1630**
68	**-0.0787**	-0.1308	**0.3492**	-0.1184	**2.6841**	0.2158	0.1747	0.1747	0.1747	0.1747	0.1747	0.1747	**2.9329**
69	-0.0200	-0.0534	0.3584	0.0823	**2.7898**	**0.3630**	**0.3254**	0.3254	0.3254	0.3254	0.3254	0.3254	-1.4164
70	0.0227	-0.0013	0.2995	0.2765	**2.8275**	**0.4864**	**0.4021**	0.4021	0.4021	0.4021	0.4021	0.4021	**-4.6373**
71	0.0121	-0.0673	0.1986	0.4611	**2.9011**	**0.4865**	0.4865	0.4865	0.4865	0.4865	0.4865	0.4865	-4.0438
72	-0.0212	-0.3399	0.0710	0.4893	**2.9540**	**0.5516**	0.5516	0.5516	0.5516	0.5516	0.5516	0.5516	-1.6199
73	-0.0277	-0.3414	0.1091	0.4632	**2.9540**	**0.5677**	0.5677	0.5677	0.5677	0.5677	0.5677	0.5677	-1.1746
74	-0.0007	-0.3159	0.3044	0.2319	**2.9581**	**0.6450**	0.6450	0.6450	0.6450	0.6450	0.6450	0.6450	-3.1793
75	-0.0124	-0.0056	0.4563	-0.0905	**3.0812**	**0.6153**	0.6153	0.6153	0.6153	0.6153	0.6153	0.6153	-2.2039
76	-0.0735	0.7908	0.7049	-0.3217	**3.2016**	**0.6925**	0.6925	0.6925	0.6925	0.6925	0.6925	0.6925	2.2299
77	-0.0767	**1.8182**	1.2226	-0.2659	**3.2815**	**0.7886**	0.7886	0.7886	0.7886	0.7886	0.7886	0.7886	1.8196
78	-0.1401	**2.6051**	1.3994	-0.1533	**3.4486**	**0.9523**	0.9523	0.9523	0.9523	0.9523	0.9523	0.9523	6.2083
79	-0.1811	**3.0472**	1.5790	0.0326	**3.6040**	**0.8182**	0.8182	0.8182	0.8182	0.8182	0.8182	0.8182	9.0304
80-90	-0.1324				**5.0667**								6.3769

Bold indicates statistical significance at the 10% level.

Table 4

Age-Centered Regression Coefficients, Female Full-Time Employment

Age Group	Age	Never Mar	Married	Lag LFP	Lag FT	1910	1920	1930	1940	1950	1960	1970	Constant
16												0.0993	**-5.6168**
17	**0.8133**	**-1.6570**	-0.0195	**0.6325**	**2.2852**						-0.3889	-0.0608	**-16.9429**
18	**0.8694**	-0.4101	0.1558	**0.6564**	**1.9512**						**-0.2160**	-0.0854	**-19.1296**
19	**0.4987**	-0.1367	0.1264	**0.6666**	**1.8383**						**-0.1087**	-0.0955	**-12.2884**
20	**0.3003**	-0.1002	-0.0147	**0.7356**	**1.8568**						-0.0084	-0.0810	**-8.3851**
21	**0.2321**	-0.1027	-0.1058	**0.7441**	**1.8663**					0.0977	0.1298	0.1298	**-7.0364**
22	**0.1705**	-0.0815	**-0.1660**	**0.7590**	**1.8660**					**0.1124**	**0.2000**	0.2000	**-5.7275**
23	**0.1226**	-0.0428	**-0.2074**	**0.8051**	**1.8469**					**0.1294**	**0.2655**	0.2655	**-4.7059**
24	**0.0835**	-0.0262	**-0.2642**	**0.8516**	**1.8280**					**0.1594**	**0.3343**	0.3343	**-3.8351**
25	**0.0628**	0.0031	**-0.2921**	**0.8840**	**1.8294**					**0.1683**	**0.3817**	0.3817	**-3.3728**
26	**0.0414**	0.0253	**-0.3079**	**0.9081**	**1.8440**					**0.1686**	**0.3950**	0.3950	**-2.8612**
27	**0.0296**	0.0367	**-0.3259**	**0.9198**	**1.8668**					**0.1590**	**0.3893**	0.3893	**-2.5503**
28	**0.0204**	0.0335	**-0.3369**	**0.8980**	**1.9171**					**0.1415**	**0.3658**	0.3658	**-2.2758**
29	**0.0175**	0.0434	**-0.3316**	**0.8583**	**1.9789**					**0.1243**	**0.3333**	0.3333	**-2.1703**
30	**0.0144**	0.0235	**-0.3396**	**0.8517**	**2.0420**					**0.1232**	**0.3040**	0.3040	**-2.0917**
31	0.0049	0.0055	**-0.3578**	**0.8440**	**2.1139**				0.0748	**0.2352**	0.2352	0.2352	**-1.8745**
32	0.0053	-0.0292	**-0.3761**	**0.8543**	**2.1881**				0.0385	**0.2096**	0.2096	0.2096	**-1.8876**
33	0.0053	-0.0772	**-0.4094**	**0.8954**	**2.2535**				0.0505	**0.2356**	0.2356	0.2356	**-1.9448**
34	**0.0129**	**-0.1244**	**-0.4253**	**0.9641**	**2.3260**				0.0690	**0.2444**	0.2444	0.2444	**-2.2917**
35	**0.0169**	**-0.1395**	**-0.4349**	**0.9961**	**2.3986**				0.0916	**0.2519**	0.2519	0.2519	**-2.4931**
36	**0.0220**	**-0.1460**	**-0.4307**	**1.0401**	**2.4617**				**0.1402**	**0.2724**	0.2724	0.2724	**-2.7763**
37	**0.0205**	**-0.1313**	**-0.4219**	**1.0422**	**2.5124**				**0.1871**	**0.2785**	0.2785	0.2785	**-2.7749**
38	**0.0175**	-0.0887	**-0.3915**	**0.9897**	**2.5547**				**0.2054**	**0.2638**	0.2638	0.2638	**-2.6602**
39	0.0141	-0.0717	**-0.3904**	**0.9422**	**2.5666**				**0.2080**	**0.2677**	0.2677	0.2677	**-2.4901**
40	**0.0153**	-0.0507	**-0.3887**	**0.9235**	**2.5645**				**0.2213**	**0.2718**	0.2718	0.2718	**-2.5300**
41	0.0122	-0.0138	**-0.3822**	**0.8579**	**2.5657**			0.0961	**0.3111**	0.3111	0.3111	0.3111	**-2.4247**
42	**0.0153**	-0.0034	**-0.3859**	**0.7901**	**2.5686**			**0.1513**	**0.3550**	0.3550	0.3550	0.3550	**-2.5298**
43	**0.0157**	0.0079	**-0.4029**	**0.7165**	**2.5788**			**0.1791**	**0.3787**	0.3787	0.3787	0.3787	**-2.4940**
44	0.0131	0.0406	**-0.4074**	**0.6174**	**2.6103**			**0.1723**	**0.3775**	0.3775	0.3775	0.3775	**-2.2995**
45	0.0057	0.0711	**-0.4154**	**0.5102**	**2.6514**			**0.1541**	**0.3698**	0.3698	0.3698	0.3698	**-1.8788**
46	0.0014	0.0852	**-0.4212**	**0.4283**	**2.6748**			**0.1331**	**0.3682**	0.3682	0.3682	0.3682	**-1.6024**
47	-0.0025	0.0563	**-0.4175**	**0.3803**	**2.6898**			**0.1089**	**0.3435**	0.3435	0.3435	0.3435	**-1.3662**

Table 4 (continued)

Age Group	Age-Centered Regression Coefficients, Female Full-Time Employment												
	Age	**Never Mar**	**Married**	**Lag LFP**	**Lag FT**	**1910**	**1920**	**1930**	**1940**	**1950**	**1960**	**1970**	**Constant**
48	0.0002	0.0016	**-0.4123**	**0.3891**	**2.6894**			**0.1058**	**0.3314**	0.3314	0.3314	0.3314	**-1.4967**
49	0.0001	-0.0170	**-0.3897**	**0.3815**	**2.6776**			0.1008	**0.3071**	0.3071	0.3071	0.3071	**-1.4903**
50	-0.0004	-0.0426	**-0.3505**	**0.3740**	**2.6541**			0.0999	**0.2723**	0.2723	0.2723	0.2723	**-1.4576**
51	-0.0082	-0.0991	**-0.3316**	**0.3910**	**2.6487**		-0.0245	0.1068	0.1068	0.1068	0.1068	0.1068	**-1.0617**
52	-0.0153	-0.0733	**-0.3112**	**0.3774**	**2.6379**		-0.0799	0.0552	0.0552	0.0552	0.0552	0.0552	-0.6399
53	-0.0170	-0.0451	**-0.2845**	**0.3414**	**2.6362**		-0.1205	0.0046	0.0046	0.0046	0.0046	0.0046	-0.4915
54	-0.0192	-0.0752	**-0.2763**	**0.3983**	**2.6365**		-0.1322	0.0043	0.0043	0.0043	0.0043	0.0043	-0.4268
55	-0.0183	-0.0768	**-0.2745**	**0.4358**	**2.6427**		**-0.1401**	0.0133	0.0133	0.0133	0.0133	0.0133	-0.5174
56	-0.0139	0.0273	**-0.2628**	**0.4304**	**2.6335**		**-0.1377**	0.0420	0.0420	0.0420	0.0420	0.0420	-0.7756
57	-0.0148	0.0904	**-0.2510**	**0.4757**	**2.6259**		-0.1060	0.0620	0.0620	0.0620	0.0620	0.0620	-0.7953
58	-0.0190	0.1894	**-0.2212**	**0.5208**	**2.6199**		-0.0849	0.0880	0.0880	0.0880	0.0880	0.0880	-0.6350
59	**-0.0394**	0.3026	**-0.1986**	**0.4701**	**2.6065**		-0.0566	0.0974	0.0974	0.0974	0.0974	0.0974	0.5665
60	**-0.0664**	**0.4089**	**-0.1827**	**0.4151**	**2.5928**		-0.0278	0.1093	0.1093	0.1093	0.1093	0.1093	**2.2028**
61	**-0.0873**	**0.4763**	**-0.1556**	**0.4290**	**2.6003**	0.2560	0.2553	0.2553	0.2553	0.2553	0.2553	0.2553	**3.1973**
62	**-0.1122**	**0.4952**	-0.1275	**0.3578**	**2.6272**	0.2731	0.2667	0.2667	0.2667	0.2667	0.2667	0.2667	**4.7414**
63	**-0.1323**	**0.4777**	**-0.1488**	0.2812	**2.6481**	0.2289	0.2442	0.2442	0.2442	0.2442	0.2442	0.2442	**6.0827**
64	**-0.1518**	**0.4682**	-0.1500	0.2047	**2.7012**	0.2220	0.2534	0.2534	0.2534	0.2534	0.2534	0.2534	**7.3650**
65	**-0.1512**	**0.4161**	-0.1498	0.2000	**2.7796**	0.1733	0.2161	0.2161	0.2161	0.2161	0.2161	0.2161	**7.3392**
66	**-0.1391**	0.3562	-0.1504	0.0748	**2.8876**	0.1169	0.1768	0.1768	0.1768	0.1768	0.1768	0.1768	**6.6428**
67	**-0.1091**	0.2999	-0.1882	0.0574	**2.9984**	0.1000	0.1692	0.1692	0.1692	0.1692	0.1692	0.1692	**4.6570**
68	**-0.0854**	0.2171	-0.1746	0.0624	**3.0863**	0.1477	0.1694	0.1694	0.1694	0.1694	0.1694	0.1694	3.0099
69	-0.0361	0.1369	-0.1815	0.1400	**3.1447**	0.1844	0.1222	0.1222	0.1222	0.1222	0.1222	0.1222	-0.4165
70	-0.0182	0.0867	-0.1492	0.1270	**3.1267**	0.1813	0.0869	0.0869	0.0869	0.0869	0.0869	0.0869	-1.6698
71	-0.0515	-0.0120	-0.0978	0.2428	**2.9377**	0.1581	0.1581	0.1581	0.1581	0.1581	0.1581	0.1581	0.6382
72	-0.0680	-0.0896	0.0329	0.2697	**2.6538**	0.0978	0.0978	0.0978	0.0978	0.0978	0.0978	0.0978	1.9232
73	-0.0678	-0.2878	0.1973	0.2643	**2.5574**	0.0936	0.0936	0.0936	0.0936	0.0936	0.0936	0.0936	1.9628
74	0.0084	-0.4295	0.4256	0.3377	**2.4492**	0.1159	0.1159	0.1159	0.1159	0.1159	0.1159	0.1159	-3.6861
75	0.0419	-0.6286	0.5964	0.4996	**2.3370**	0.2488	0.2488	0.2488	0.2488	0.2488	0.2488	0.2488	-6.3886
76	0.0641	-0.4931	0.6000	0.5508	**2.4080**	0.3768	0.3768	0.3768	0.3768	0.3768	0.3768	0.3768	-8.2154
77	0.0635	-0.2593	0.6729	0.7069	**2.5606**	0.5600	0.5600	0.5600	0.5600	0.5600	0.5600	0.5600	-8.4781
78	0.0021	0.1850	0.6702	0.8128	**2.4981**	0.6806	0.6806	0.6806	0.6806	0.6806	0.6806	0.6806	-3.9291
79	-0.0572	-0.0657	0.4936	0.8152	**2.2260**	0.7999	0.7999	0.7999	0.7999	0.7999	0.7999	0.7999	0.7435
80-90	-0.2909				1.7717								20.8113

Bold indicates statistical significance at the 10% level.

Figure 7. Average Part-Time Hours by Age and Sex, CPS 1984-1998

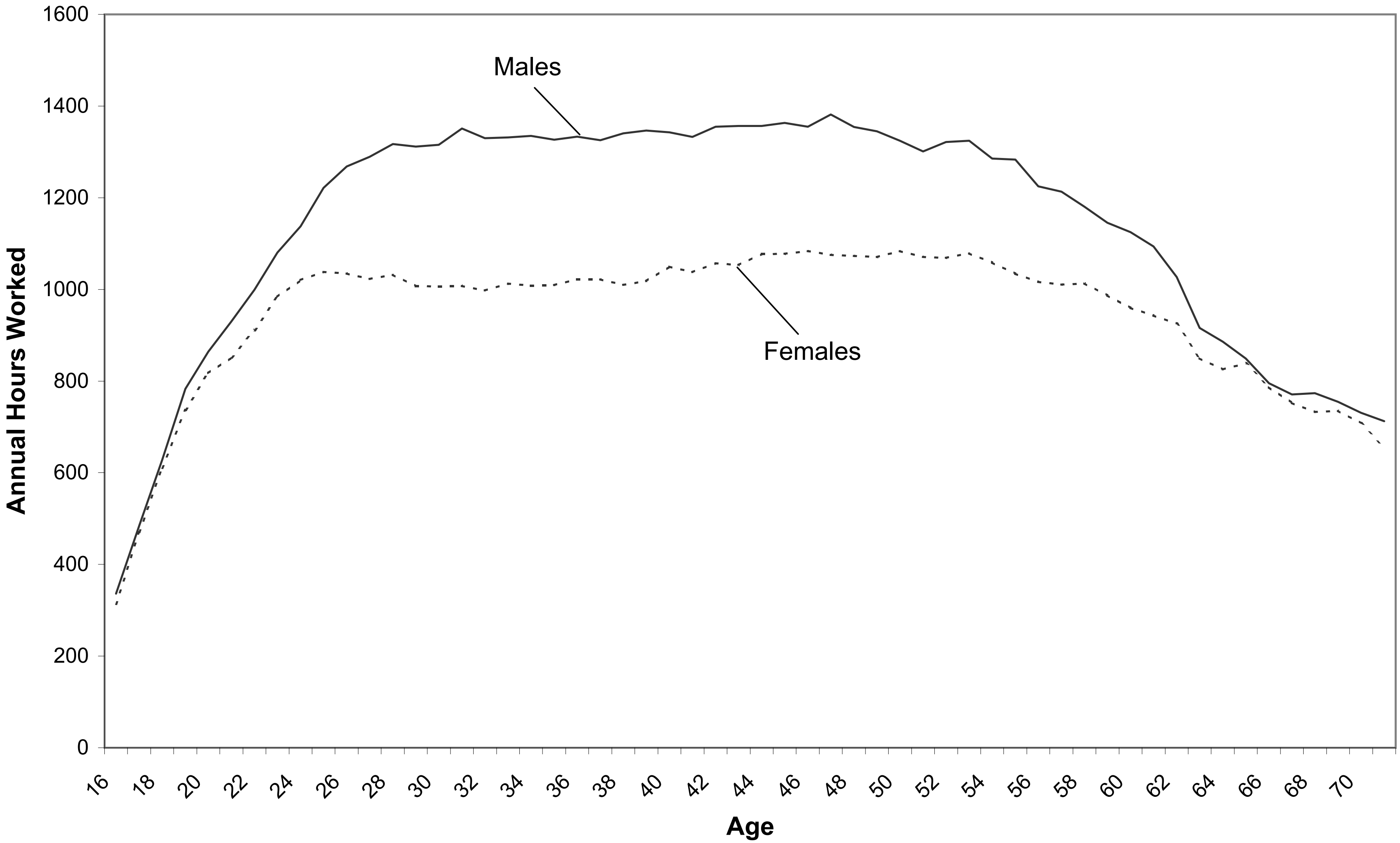

Figure 8. Projected Average Annual Hours Worked, 2002-2076

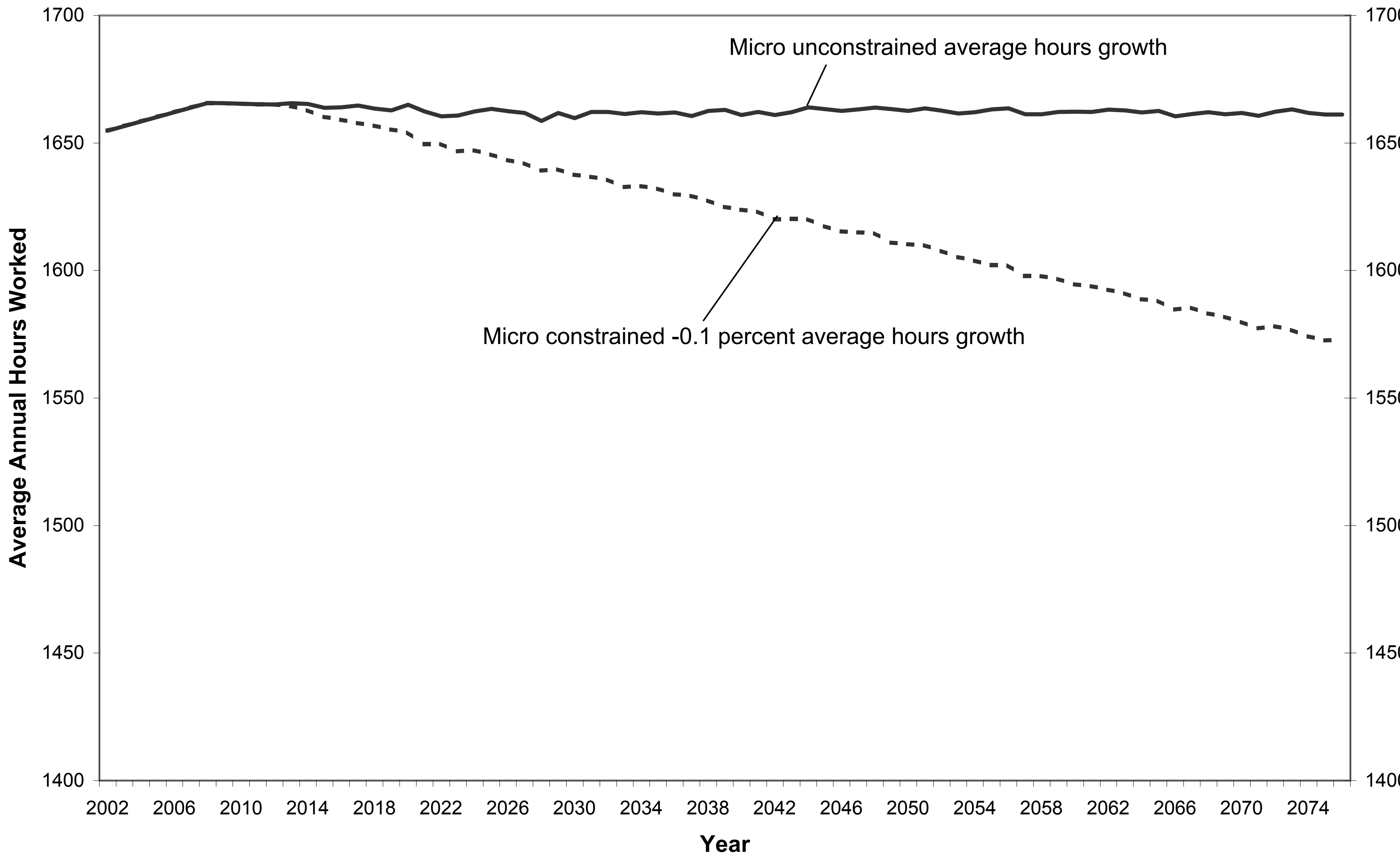

Figure 9. Male Cohort Mean Earnings, PSID 1968-1992

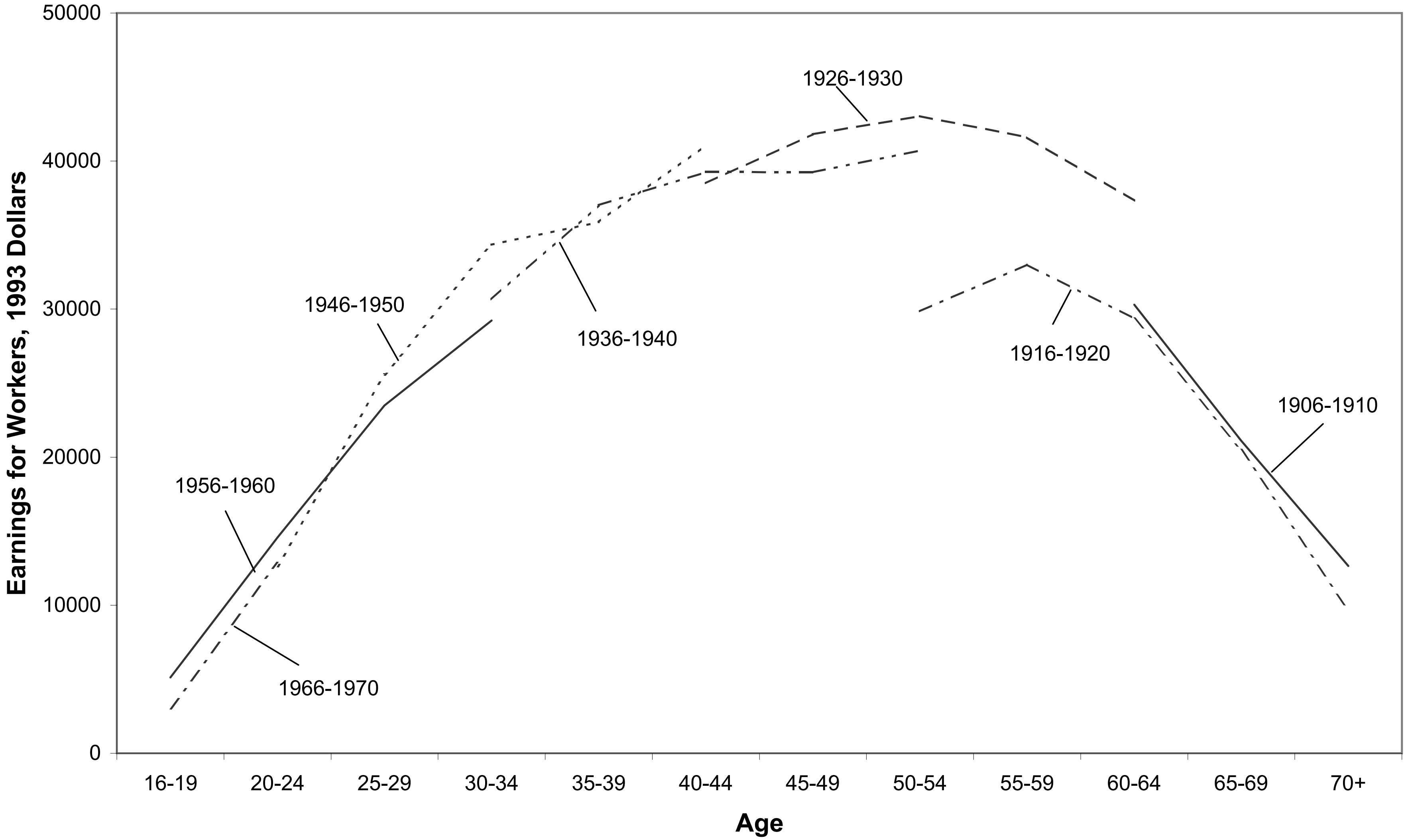

Figure 10. Female Cohort Mean Earnings, PSID 1968-1992

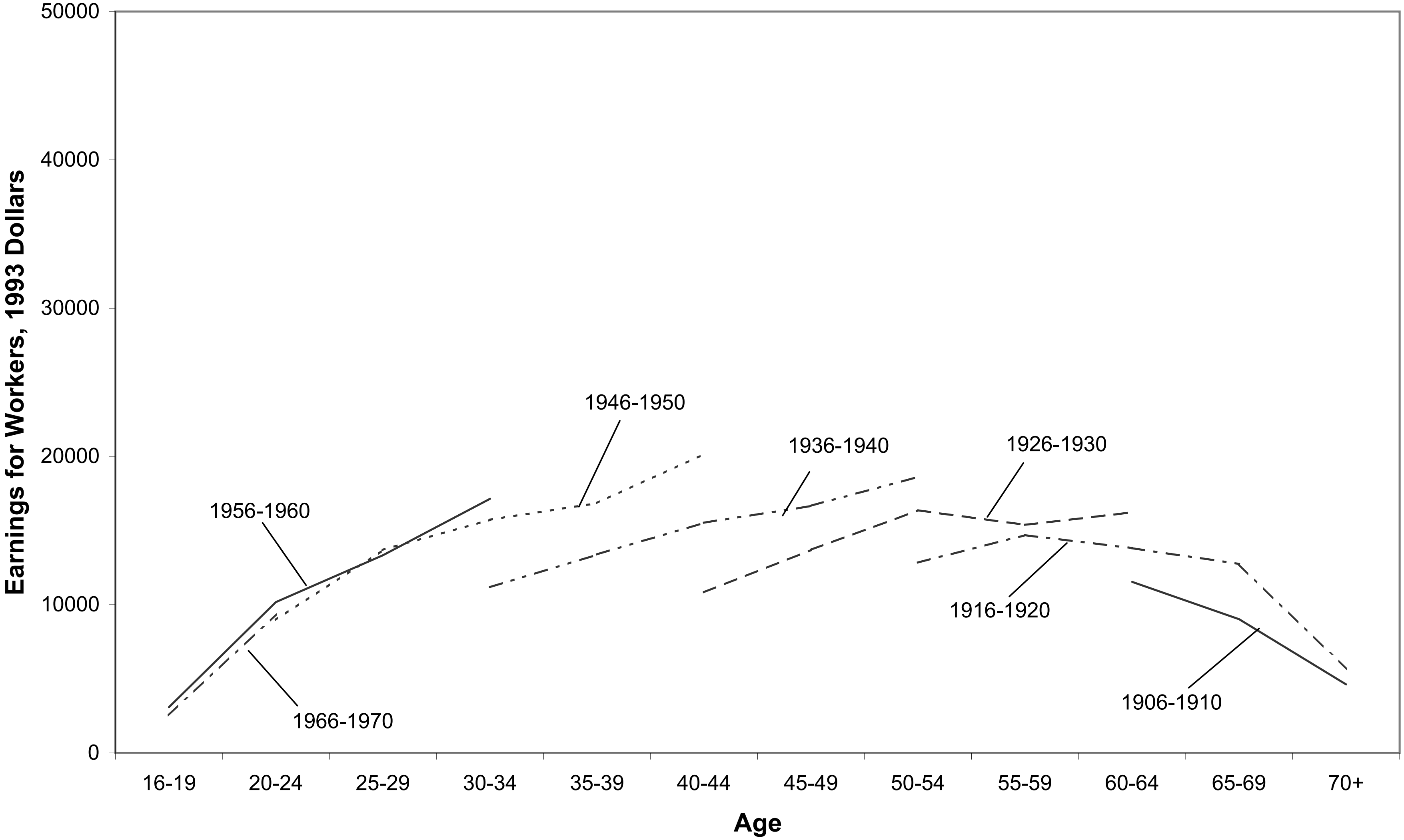

Table 5
Log FTE Earnings Regression Coefficients

	Males		Females	
	Low Educated	High Educated	Low Educated	High Educated
Constant	**10.202**	**10.202**	**9.435**	**9.435**
Age				
16	**-1.235**	-1.203	**-1.148**	-1.153
17	**-1.244**	-1.210	**-1.167**	**-0.956**
18	**-1.086**	-1.148	**-0.963**	-0.881
19	**-0.852**	**-1.016**	**-0.685**	-0.672
20	**-0.623**	**-0.859**	**-0.507**	-0.551
21	**-0.507**	**-0.739**	**-0.418**	-0.463
22	**-0.434**	**-0.607**	**-0.350**	-0.309
23	**-0.326**	**-0.399**	**-0.324**	**-0.129**
24	**-0.255**	-0.269	**-0.316**	**0.059**
25	**-0.247**	-0.181	**-0.345**	**0.143**
26	**-0.212**	**-0.039**	**-0.338**	**0.227**
27	**-0.151**	**0.058**	**-0.259**	**0.241**
28	**-0.141**	**0.097**	**-0.292**	**0.279**
29	**-0.119**	**0.187**	**-0.227**	**0.298**
30	**-0.134**	**0.253**	**-0.245**	**0.317**
31	**-0.133**	**0.289**	**-0.244**	**0.336**
32	**-0.079**	**0.331**	**-0.213**	**0.328**
33	**-0.089**	**0.368**	**-0.210**	**0.339**
34	**-0.059**	**0.392**	**-0.173**	**0.349**
35	**-0.095**	**0.410**	**-0.126**	**0.373**
36	**-0.080**	**0.436**	**-0.168**	**0.402**
37	-0.048	**0.450**	**-0.118**	**0.391**
38	-0.050	**0.445**	**-0.123**	**0.456**
39	-0.010	**0.497**	**-0.091**	**0.436**
40	-0.024	**0.526**	-0.061	**0.425**
41	-0.023	**0.547**	**-0.071**	**0.459**
42	-0.014	**0.552**	**-0.083**	**0.488**
43	-0.006	**0.531**	-0.037	**0.519**
44	0.032	**0.514**	-0.052	**0.520**
45	0.000	**0.552**	0.000	**0.526**

Table 5 (continued)
Log FTE Earnings Regression Coefficients

	Males		**Females**	
	Low Educated	**High Educated**	**Low Educated**	**High Educated**
46	-0.011	**0.609**	-0.001	**0.433**
47	0.000	**0.580**	0.030	**0.528**
48	-0.005	**0.600**	-0.005	**0.520**
49	-0.016	**0.595**	0.038	**0.563**
50	-0.023	**0.591**	0.033	**0.628**
51	-0.062	**0.595**	0.022	**0.634**
52	-0.041	**0.565**	0.028	**0.603**
53	-0.033	**0.566**	0.065	**0.618**
54	-0.058	**0.564**	**0.091**	**0.596**
55	**-0.080**	**0.568**	**0.125**	**0.705**
56	**-0.069**	**0.555**	**0.098**	**0.644**
57	-0.058	**0.525**	0.032	**0.692**
58	**-0.077**	**0.547**	0.053	**0.712**
59	**-0.123**	**0.544**	0.055	**0.713**
60	**-0.111**	**0.505**	0.019	**0.727**
61	**-0.118**	**0.381**	0.002	**0.706**
62	**-0.159**	**0.415**	0.002	**0.702**
63	**-0.212**	**0.368**	0.041	**0.892**
64	**-0.265**	**0.418**	**-0.153**	**0.600**
65	**-0.325**	**0.109**	**-0.131**	**0.451**
66	**-0.482**	**0.102**	**-0.196**	**0.617**
67	**-0.723**	**-0.061**	**-0.430**	**0.459**
68	**-0.736**	**-0.331**	**-0.302**	**0.474**
69	**-0.839**	**-0.522**	**-0.402**	**0.158**
70	**-0.934**	-0.845	**-0.633**	**0.036**
Cohort				
1940's	**-0.029**	-0.049	**0.228**	0.203
1950's	**-0.137**	-0.135	**0.260**	**0.201**
1960's	**-0.385**	**-0.227**	**0.129**	0.167

For low-educated columns, bold indicates statistical significance at the 10% level.
For high-educated columns, bold indicates statistical difference from low-educated at the 10% level.

Figure 11. Male Cohort Mean Earnings, CWHS 1984-1998

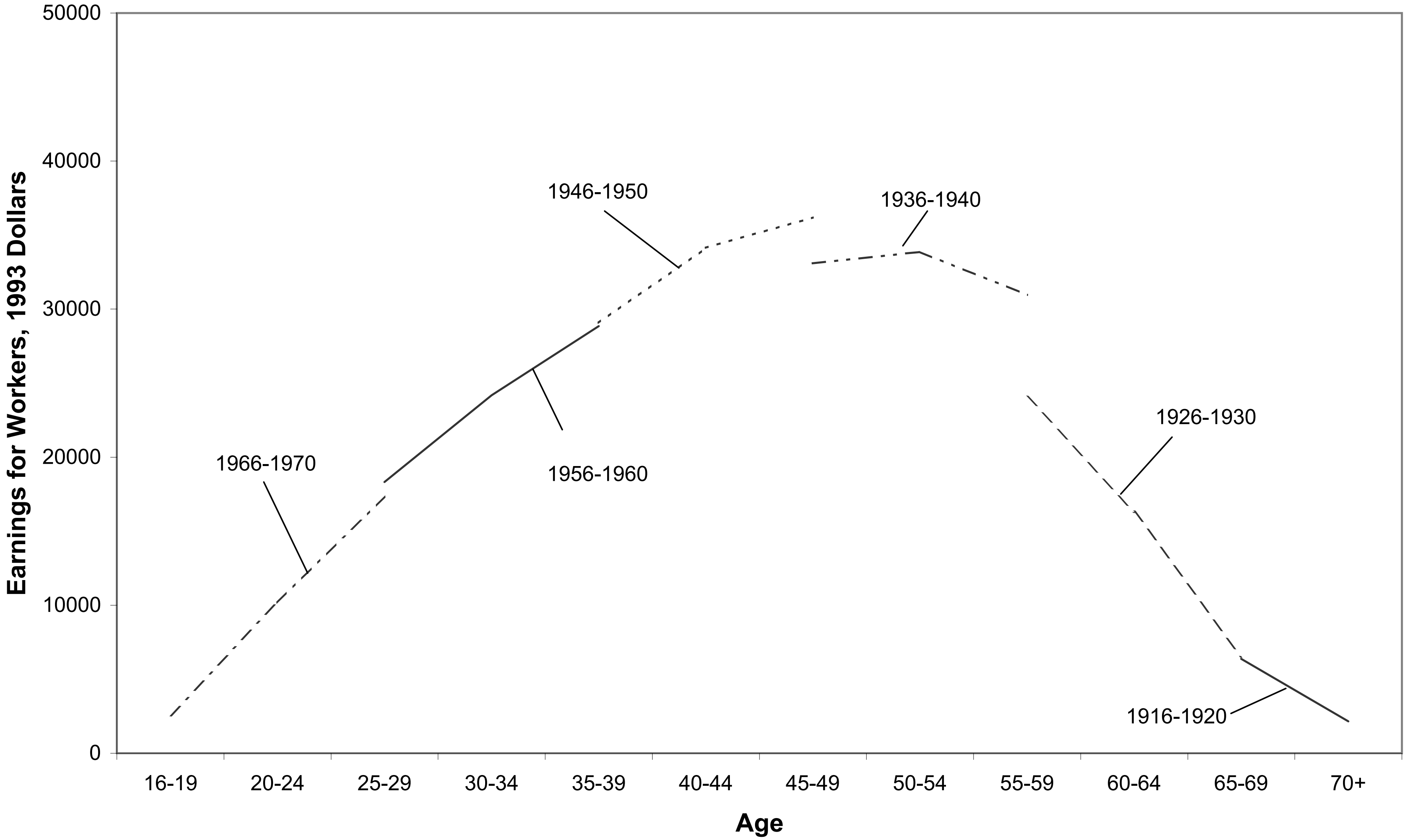

Figure 12. Female Cohort Mean Earnings, CWHS 1984-1998

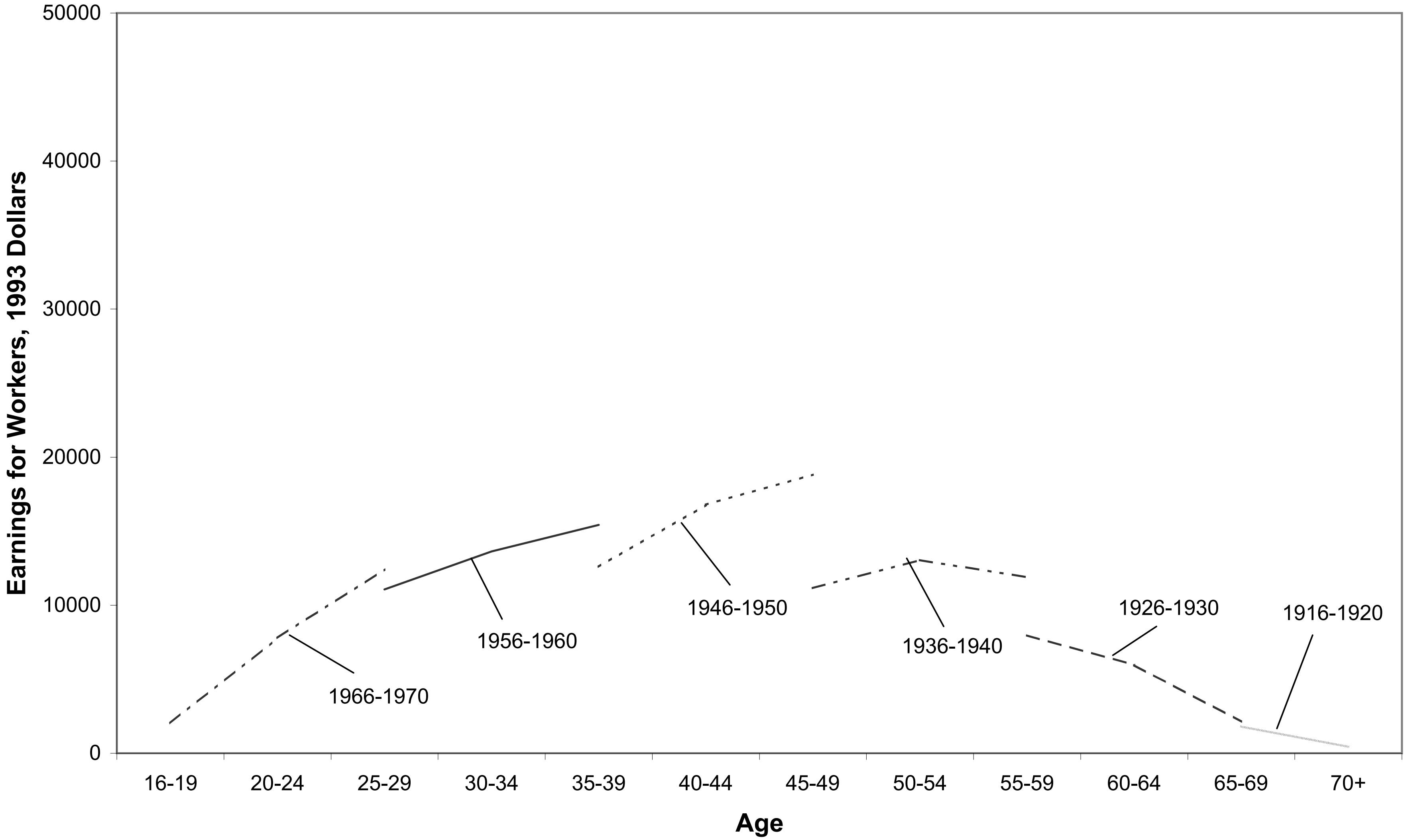

Table 6
Variance of Unexplained Earnings Changes
(CWHS Data, Ages 25 to 55, 1984 to 1998)

Year Gap	Men	Women
1	0.329	0.406
2	0.446	0.562
3	0.502	0.626
4	0.541	0.664
5	0.571	0.691
6	0.592	0.706
7	0.603	0.710
8	0.615	0.712
9	0.623	0.711
10	0.626	0.702
11	0.632	0.698
12	0.625	0.687
13	0.617	0.662
14	0.605	0.634

Table 7
Solving for Base Variance of Permanent Earnings Differentials
(CWHS Data, 1998)

	Men	Women
Base-Year Residual Variance	0.9706	0.8582
Less: Transitory Variance	0.1225	0.1600
Less: Weighted Average Age	20.2715	19.9585
*Permanent Variance	*0.0100	*0.0036
	0.2027	0.0719
Equals: Base Variance of Permanent Earnings Differentials	0.6454	0.6264

Table 8
1995 Labor Force Participation Rates, CWHS versus CPS

	Males		Females	
Age	**CWHS**	**CPS**	**CWHS**	**CPS**
16-19	66.7	50.8	66.3	50.6
20-24	84.0	84.3	80.2	74.7
25-29	86.6	91.2	79.5	77.6
30-34	84.7	92.4	75.6	75.9
35-39	85.8	91.9	76.8	76.9
40-44	86.3	90.6	79.8	79.8
45-49	85.4	90.3	80.2	78.7
50-54	81.5	87.0	71.7	73.4
55-59	75.4	80.3	61.6	61.6
60-64	57.7	60.8	44.3	44.0
65-69	33.2	32.7	22.9	19.9
70-90	14.4	13.1	6.6	6.2

Table 9
Share with 14+ Years of Education, CWHS versus CPS

	Males		Females	
Birth Cohort	**CWHS**	**CPS**	**CWHS**	**CPS**
1905-1909	15.53	14.23	13.19	12.30
1915-1919	19.02	17.69	14.26	13.58
1925-1929	25.44	24.49	16.18	16.02
1935-1939	29.85	29.46	21.85	21.57
1945-1949	40.94	41.27	33.71	33.95
1955-1959	39.26	39.01	40.37	39.98
1965-1969	41.61	42.01	45.02	44.50

Figure 13. Low-Educated Male Cohort Mean Earnings, PSID 1968-1992

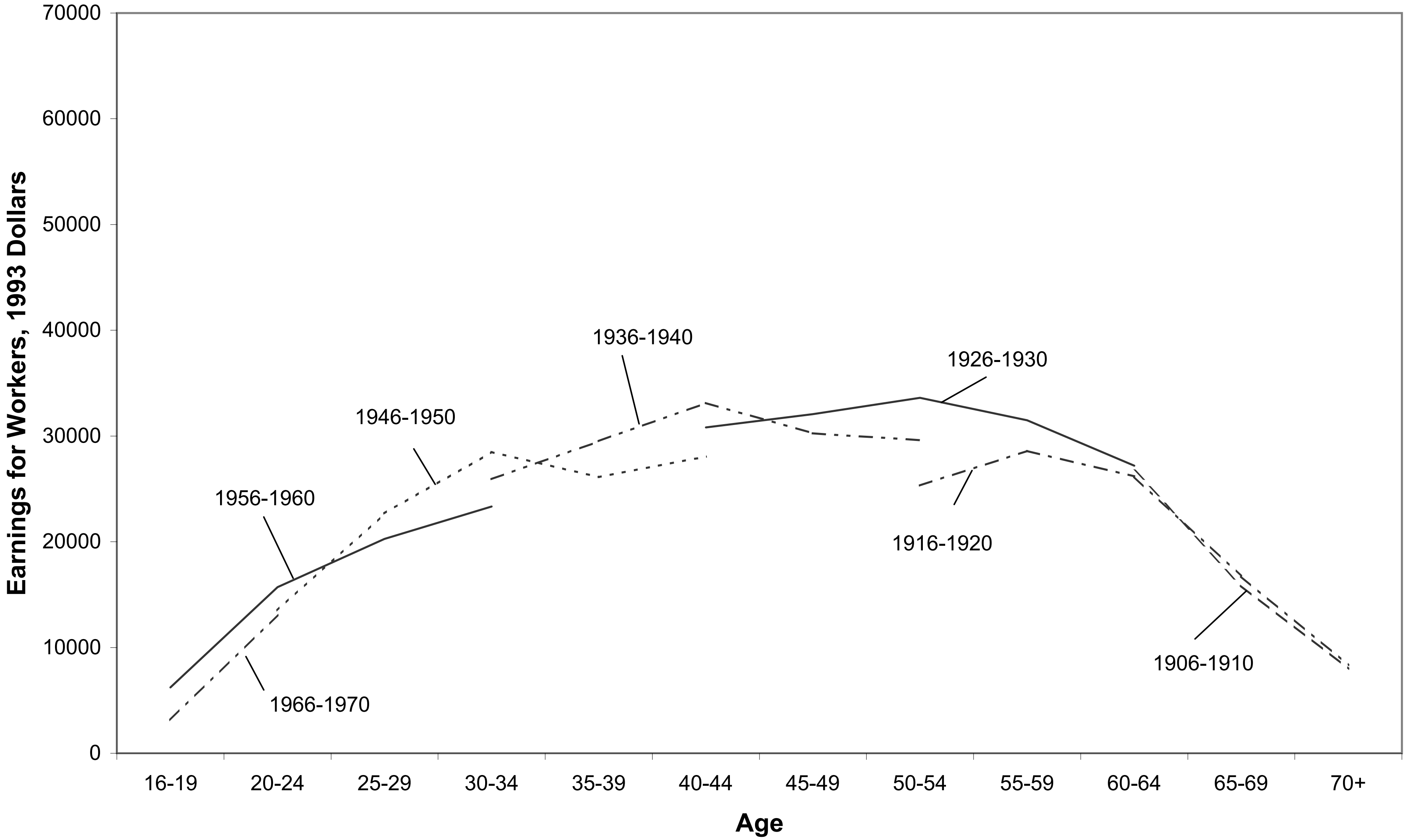

Figure 14. High-Educated Male Cohort Mean Earnings, PSID 1968-1992

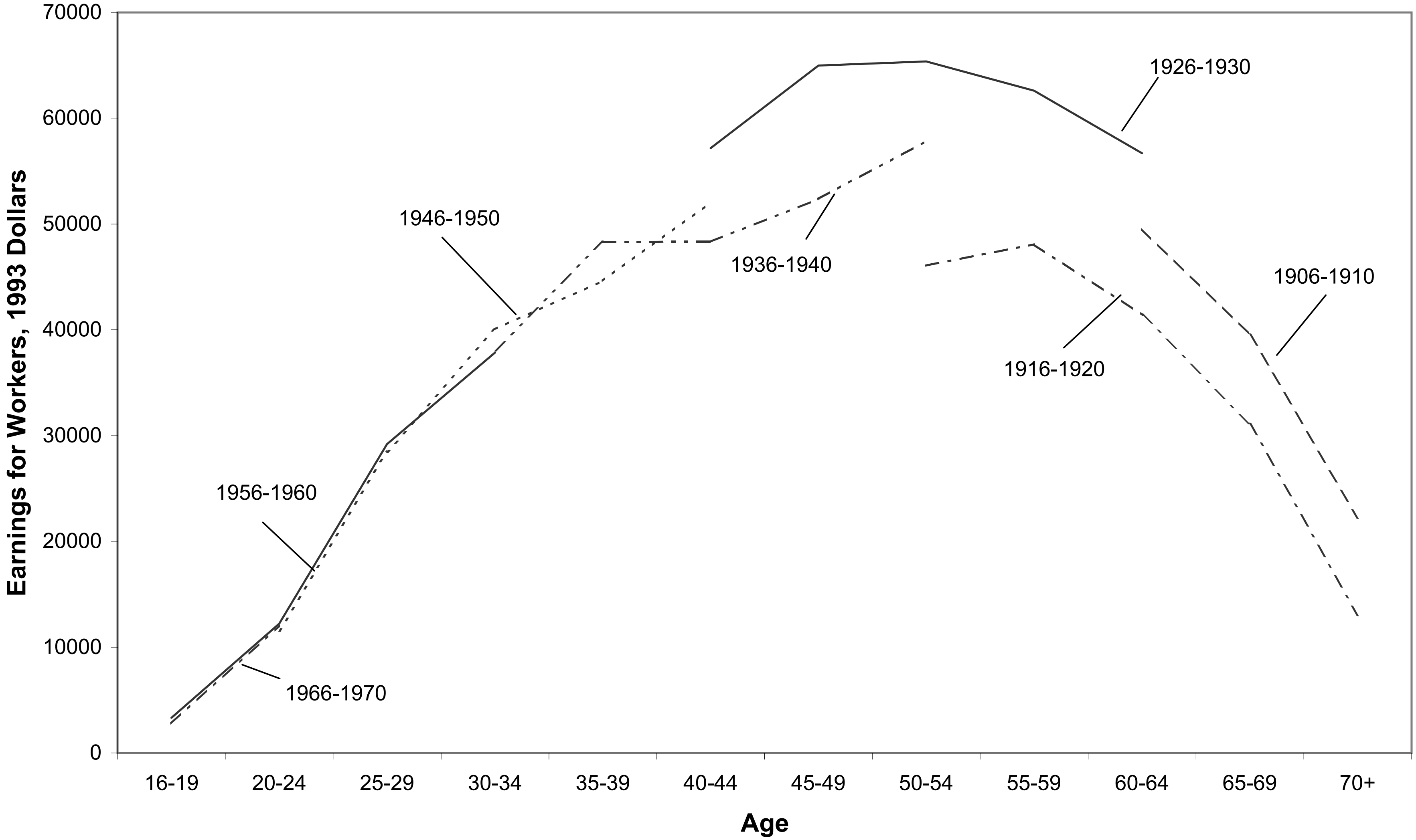

Figure 15. Low-Educated Female Cohort Mean Earnings, PSID 1968-1992

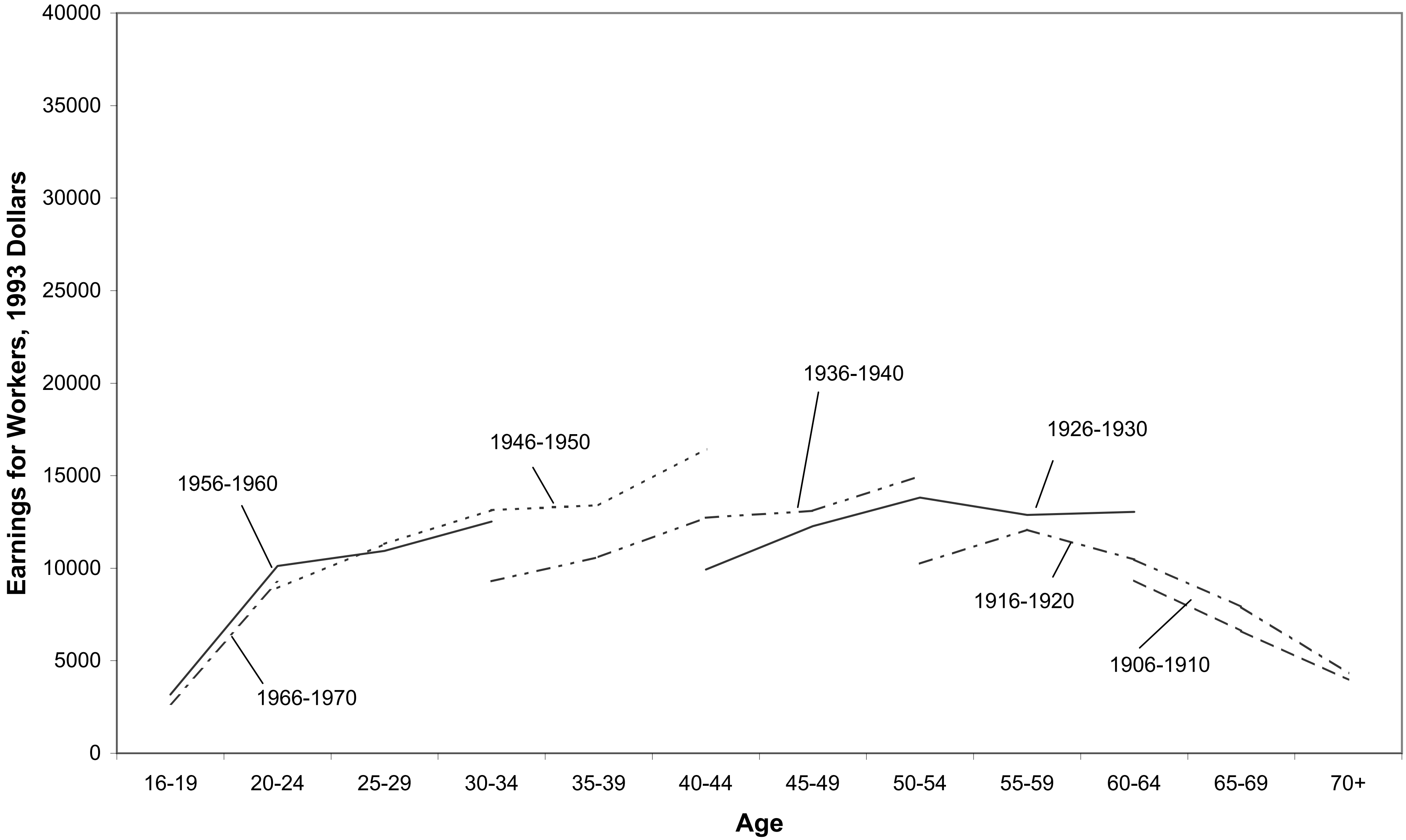

Figure 16. High-Educated Female Cohort Mean Earnings, PSID 1968-1992

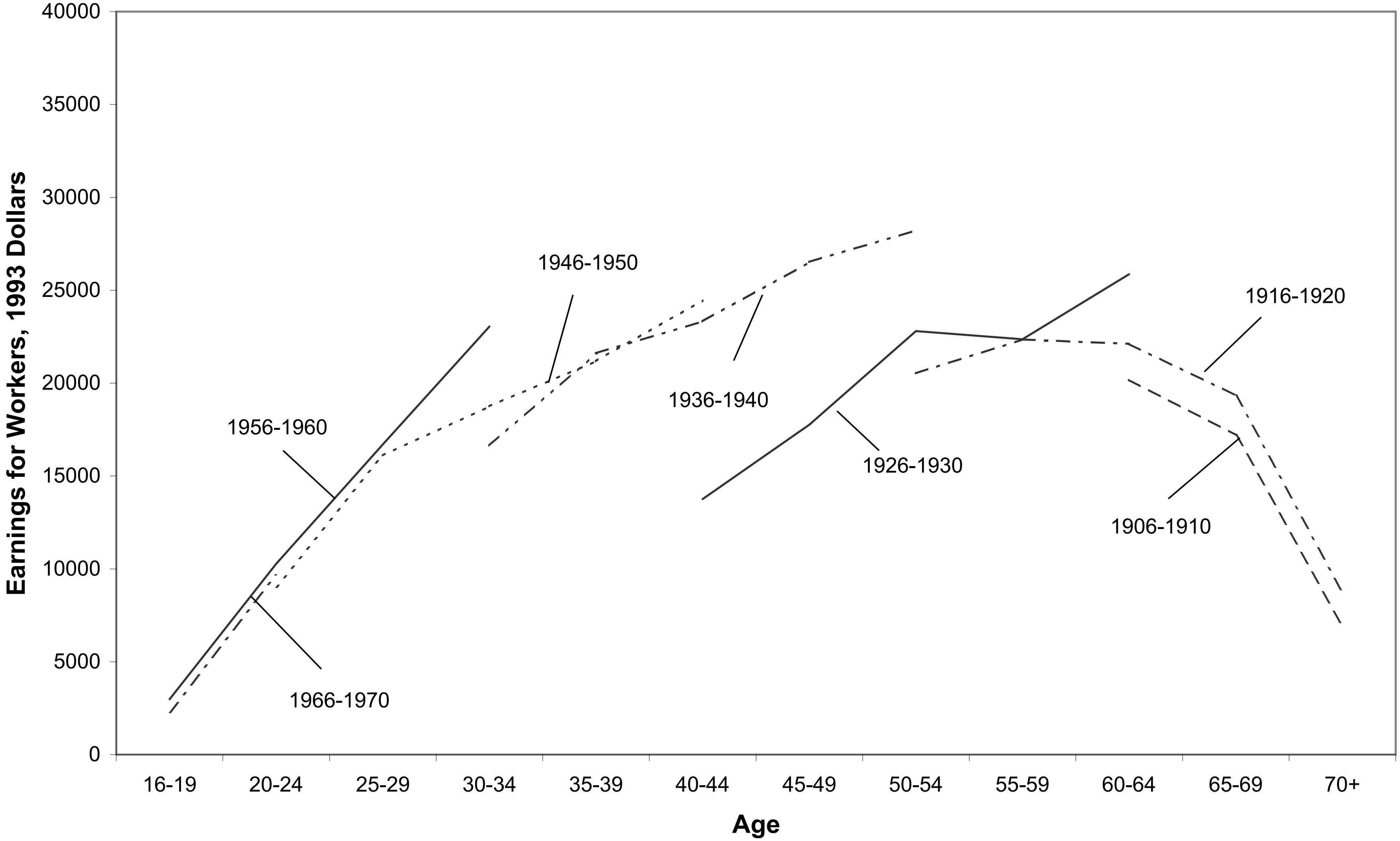

Figure 17. Low-Educated Male Cohort Mean Earnings, CWHS 1984-1998

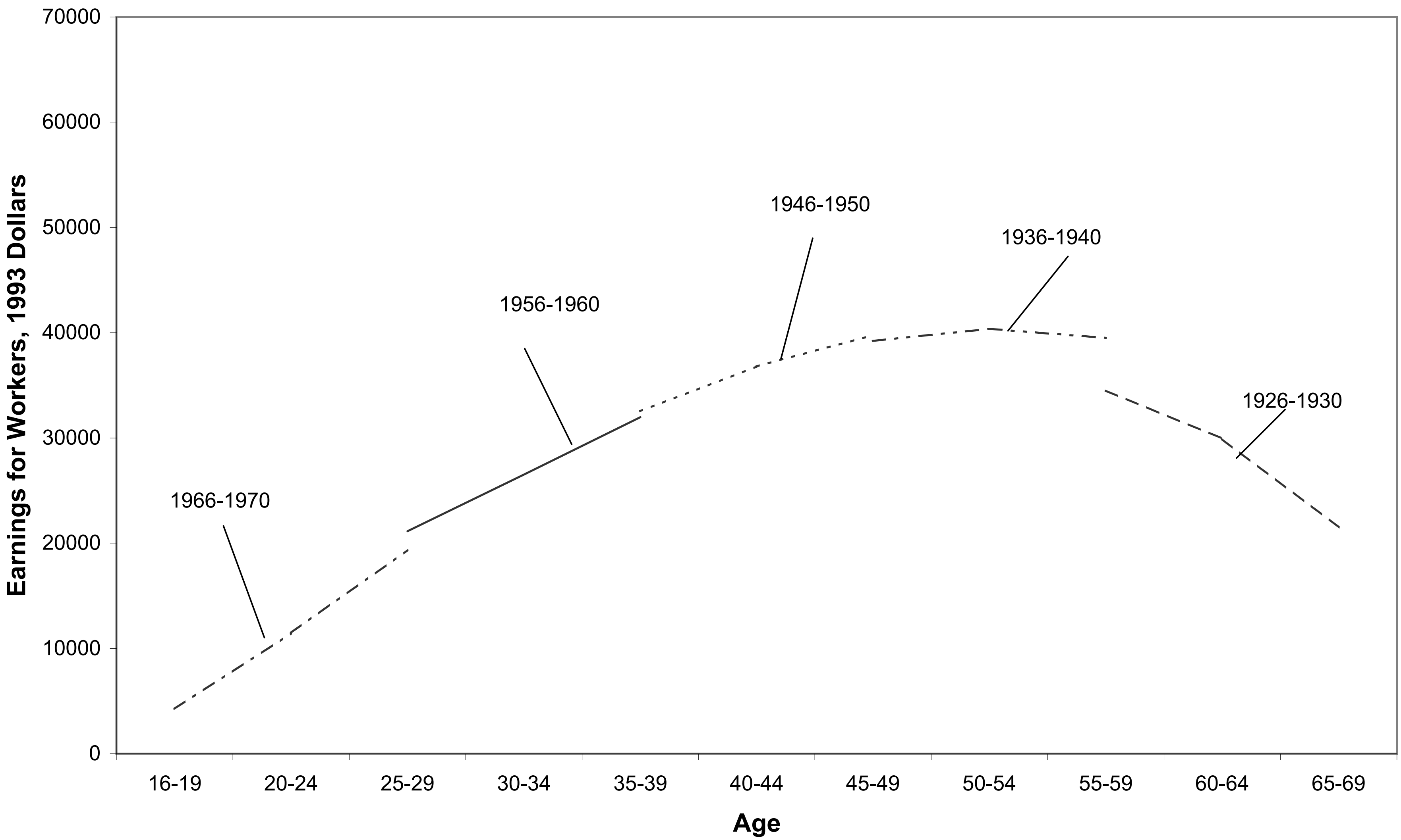

Figure 18. High-Educated Male Cohort Mean Earnings, CWHS 1984-1998

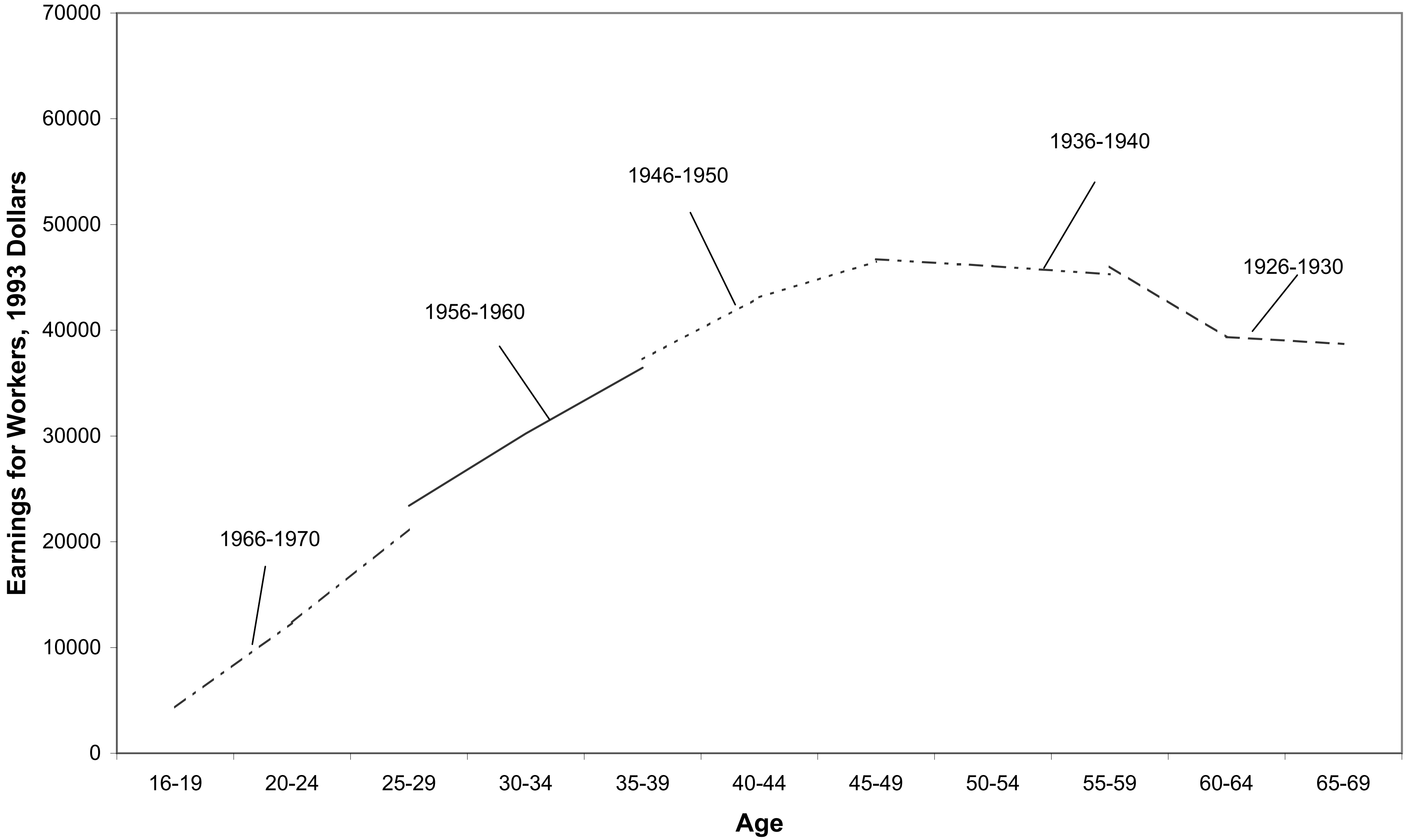

Figure 19. Low-Educated Female Cohort Mean Earnings, CWHS 1984-1998

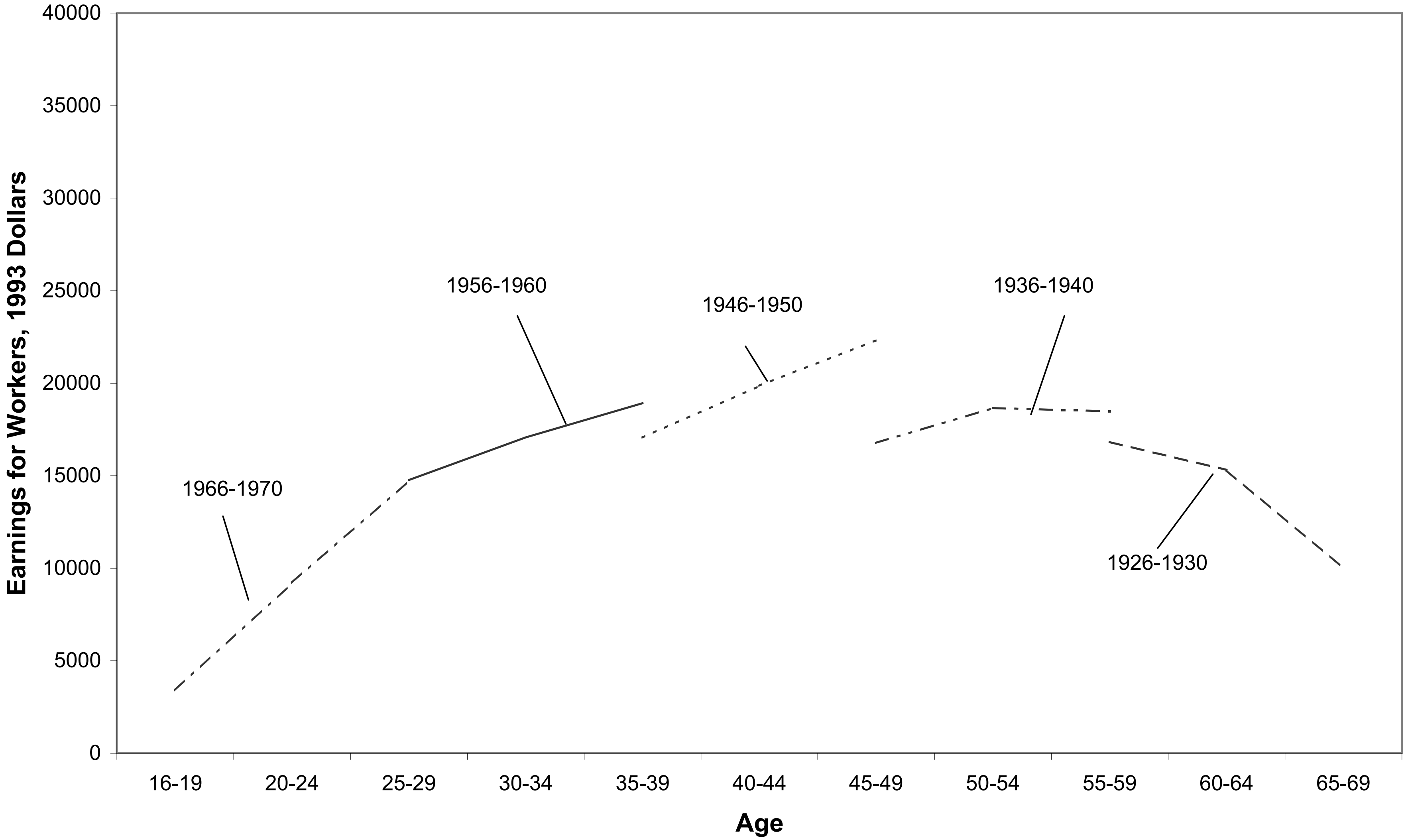

Figure 20. High-Educated Female Cohort Mean Earnings, CWHS 1984-1998

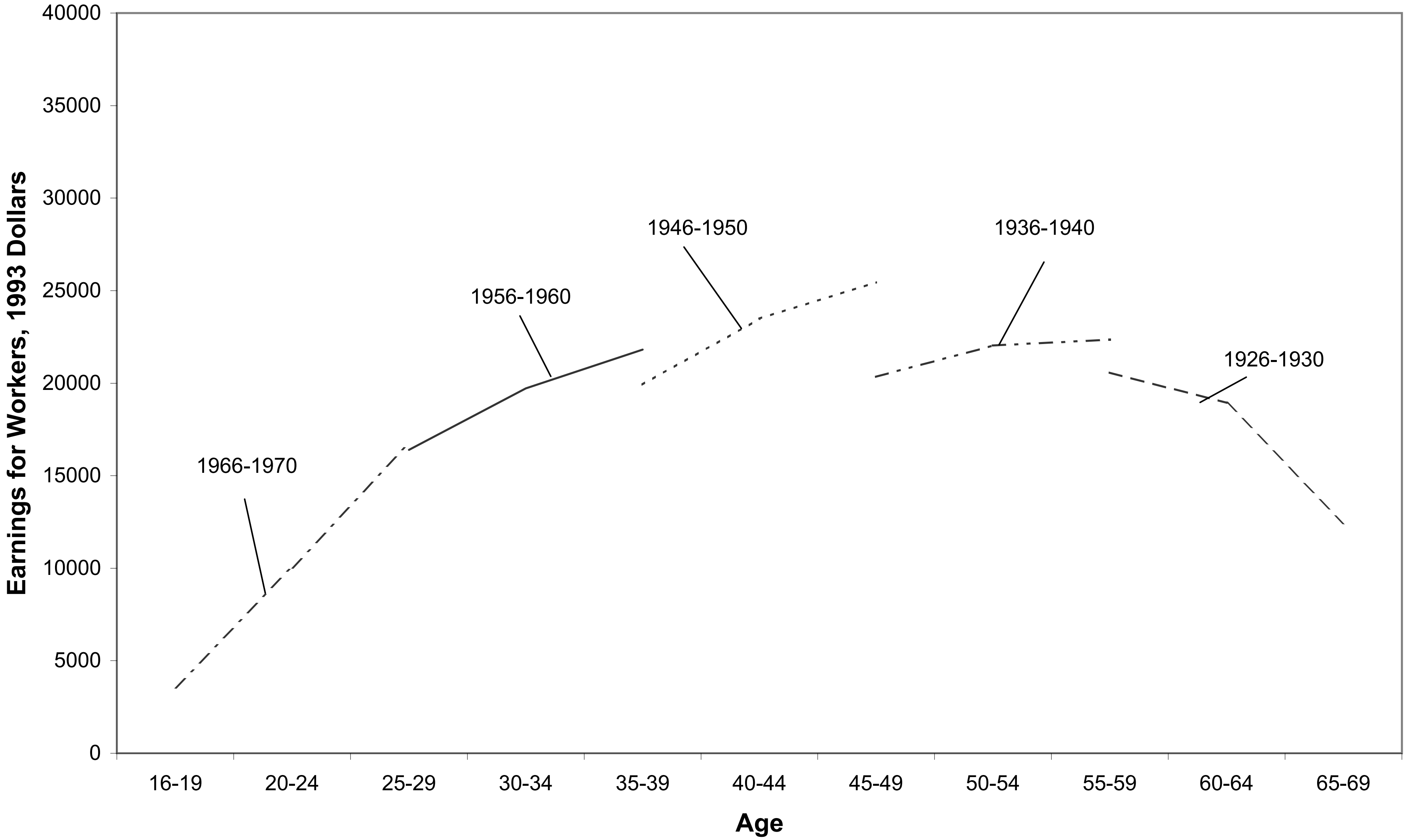

Figure 21. Male Cohort Labor Force Participation, CWHS Historical and Projected

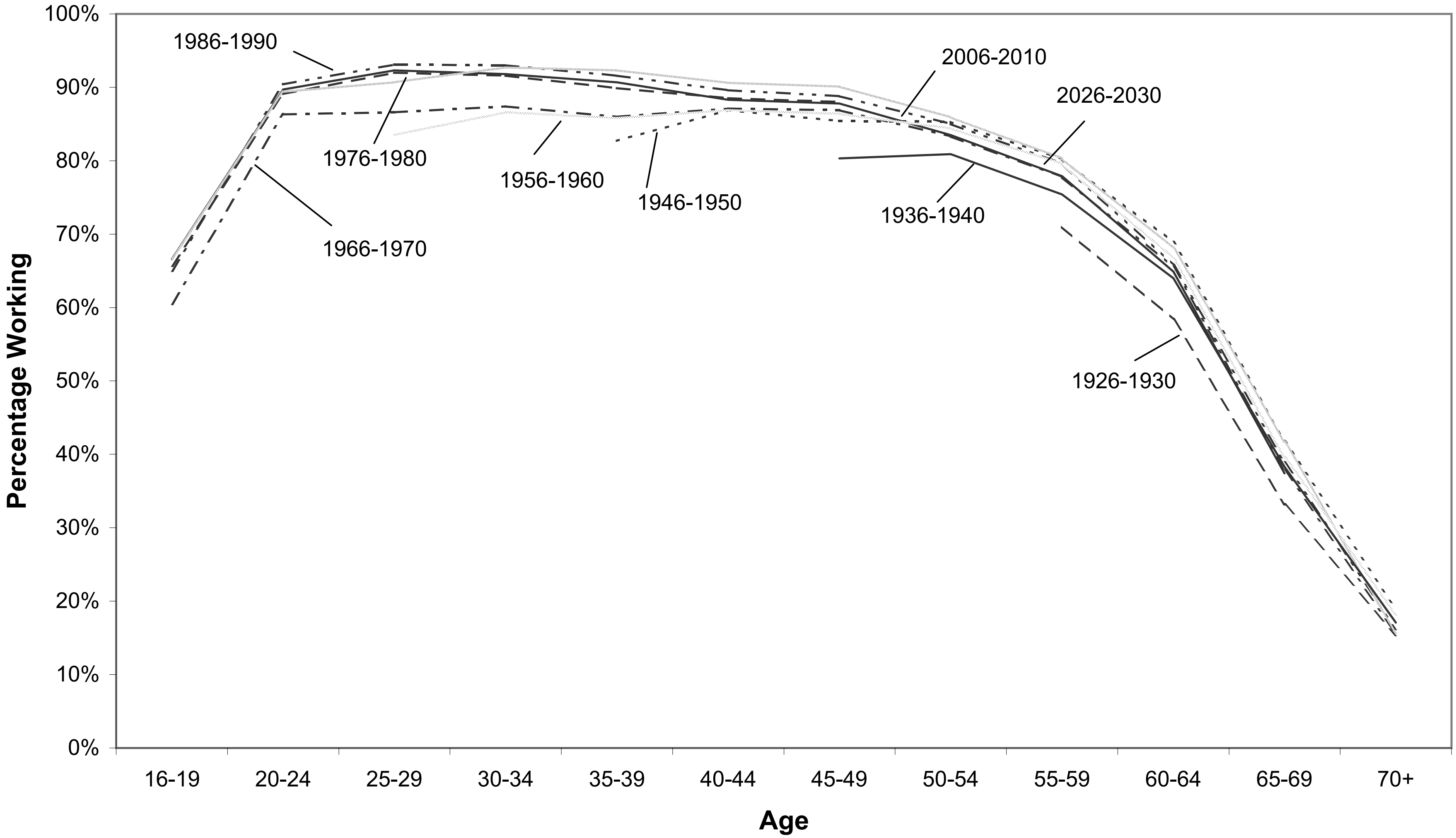

Figure 22. Female Cohort Labor Force Participation, CWHS Historical and Projected

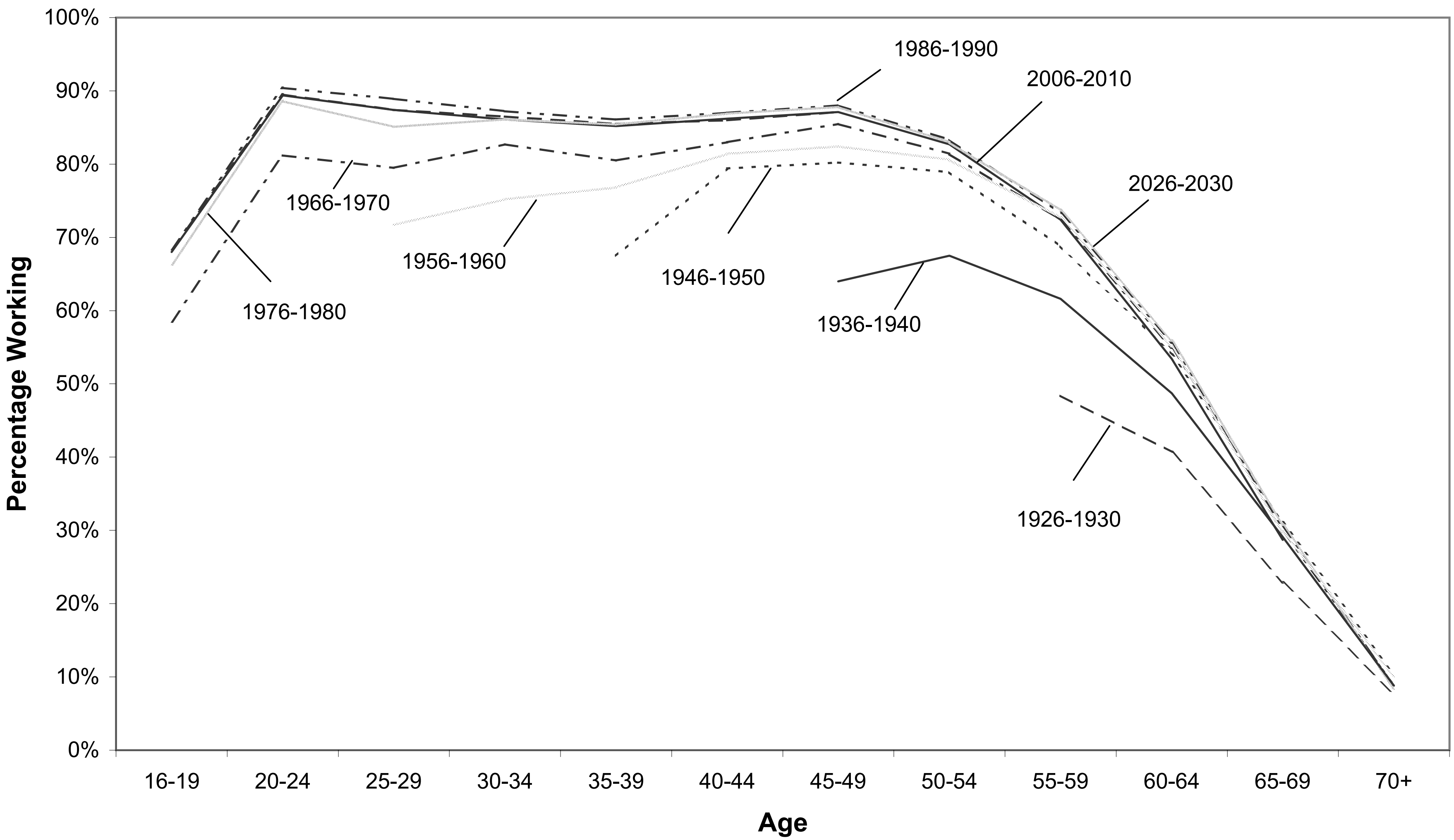

Figure 23. Projected Longitudinal Labor Force Participation for 62-year-old Males

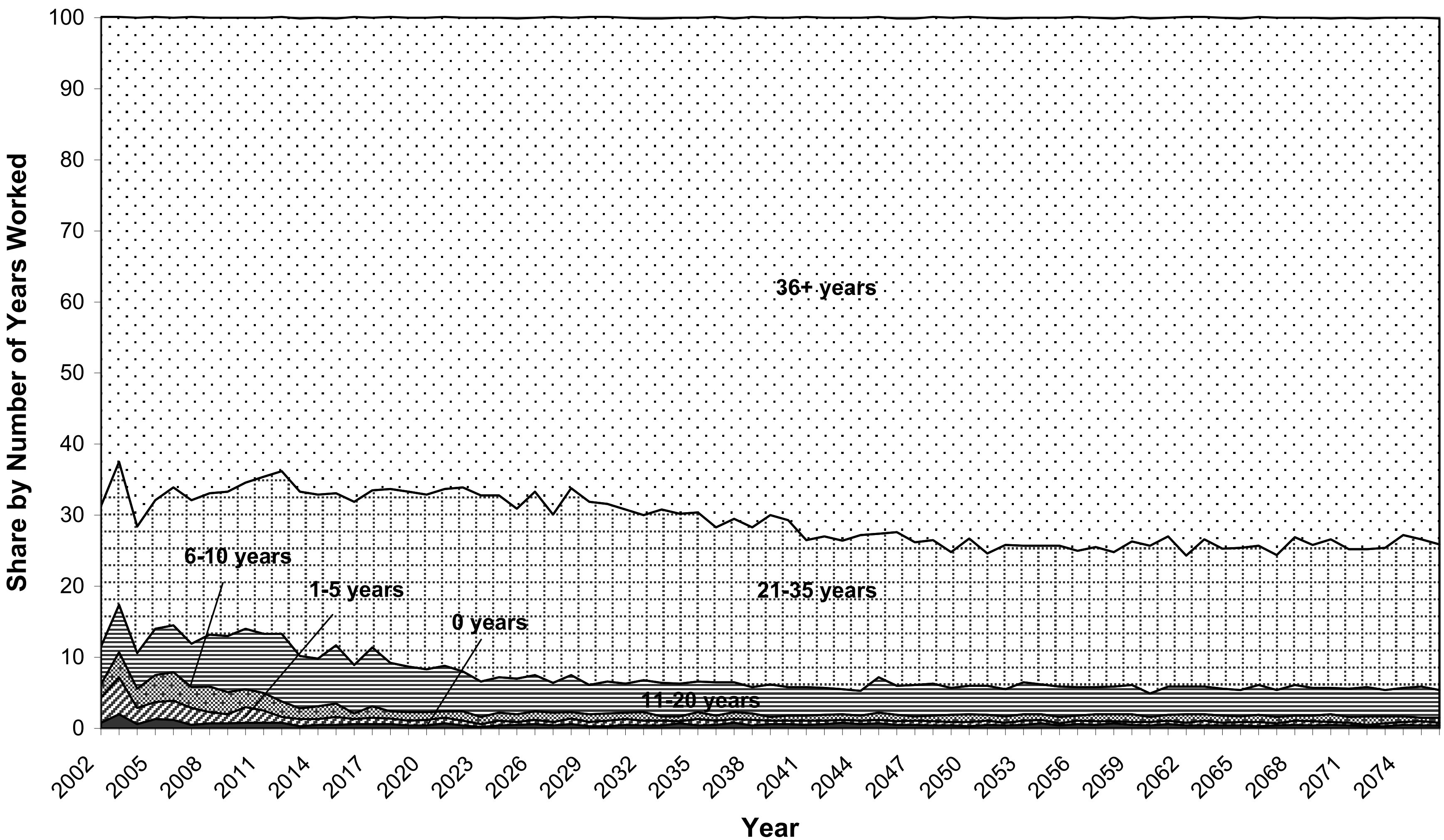

Figure 24. Projected Longitudinal Labor Force Participation for 62-year-old Females

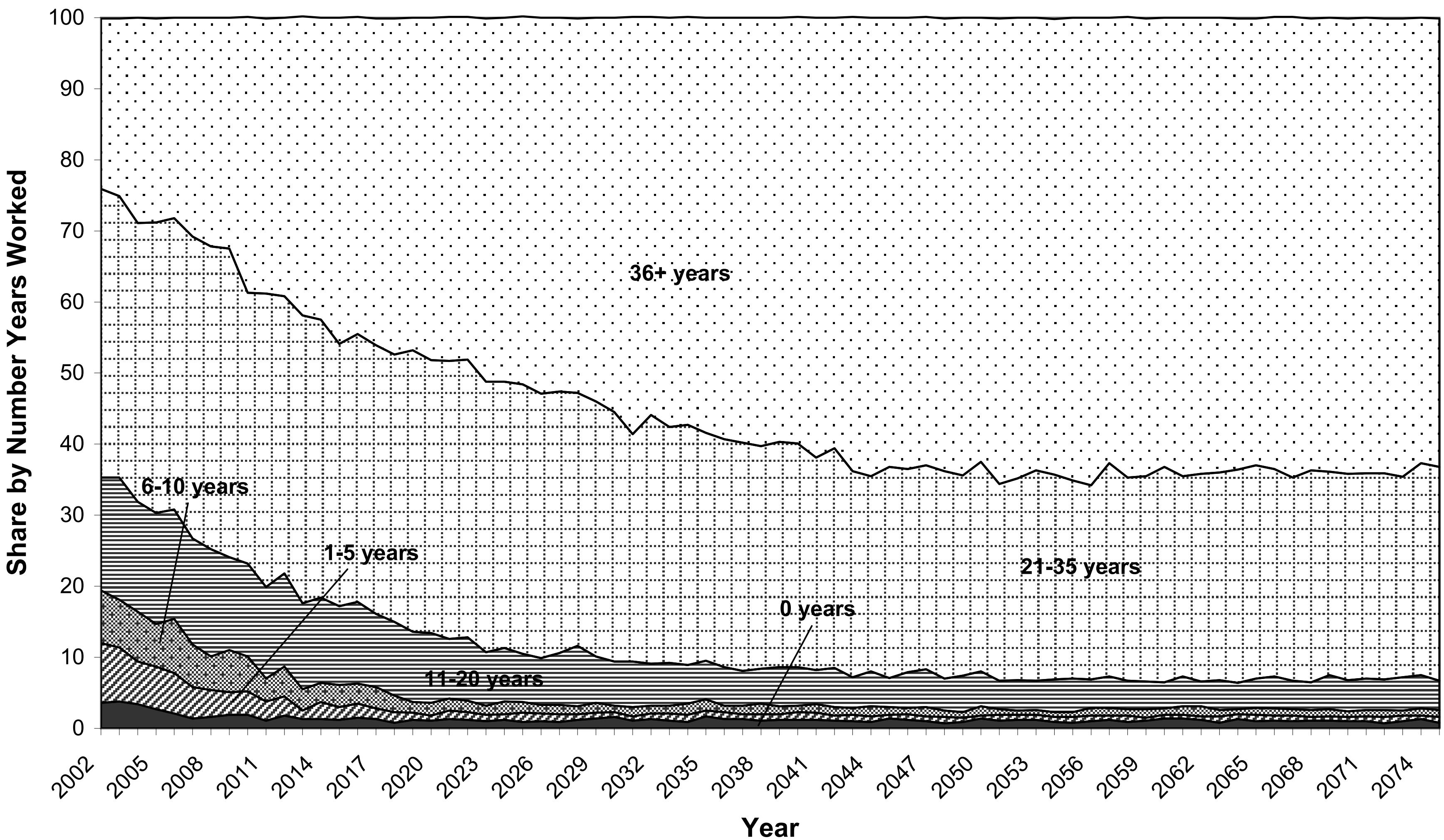

Figure 25. Male Cohort Full-Time Employment
CWHS Historical and Projected

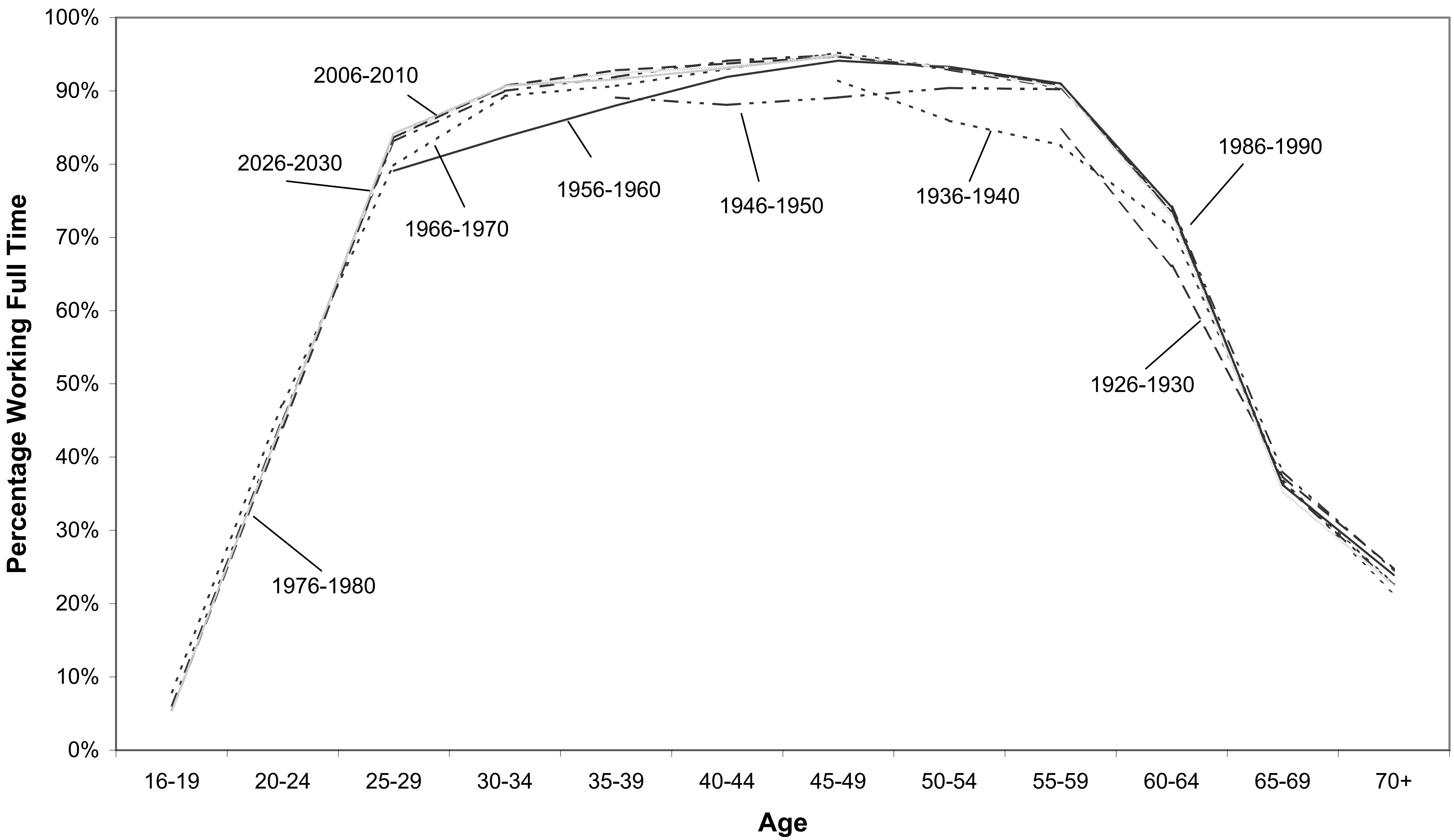

Figure 26. Female Cohort Full-Time Employment CWHS Historical and Projected

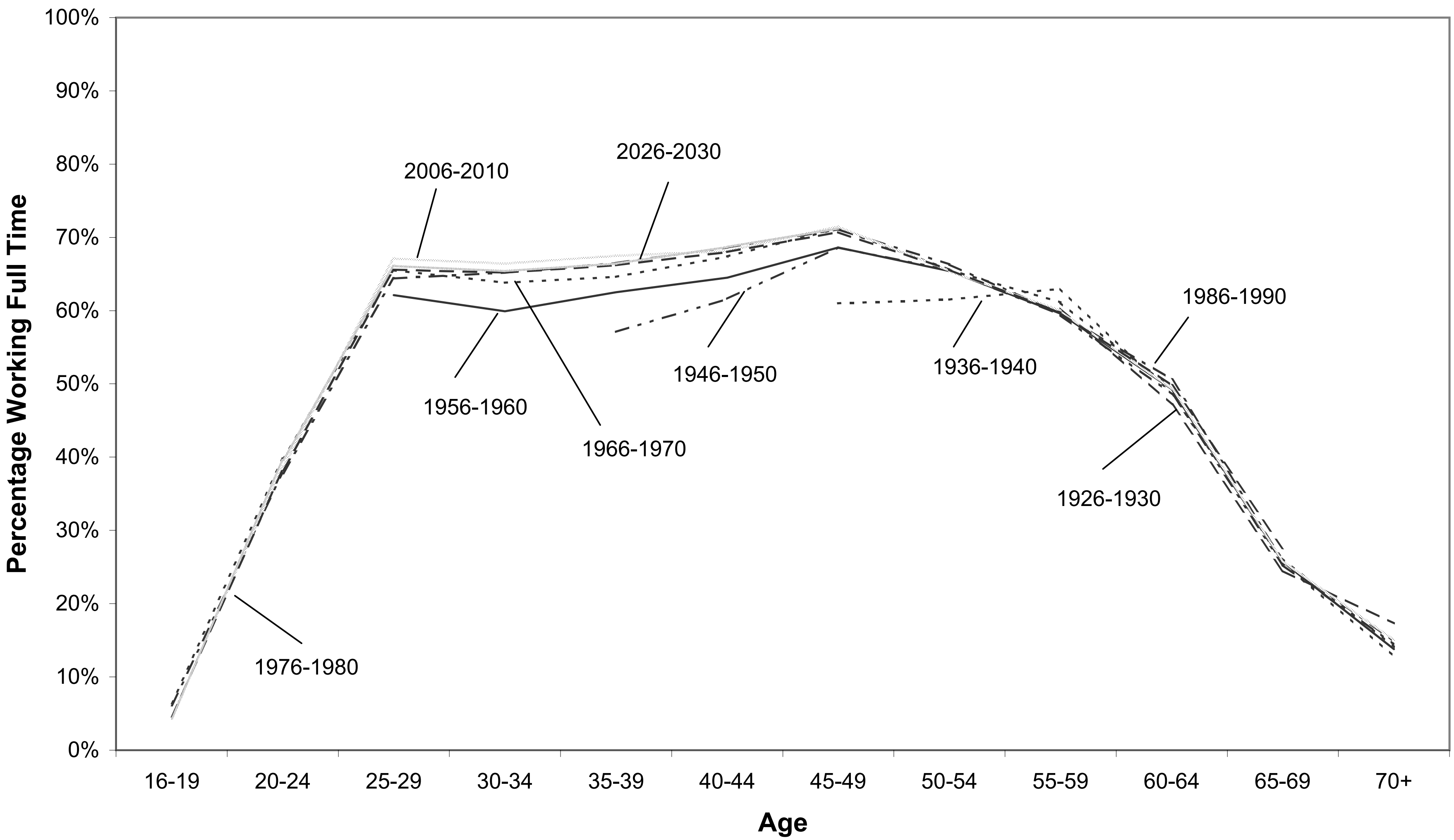

Figure 27. Low-Educated Male Cohort Mean Earnings, CWHS Historical and Projected

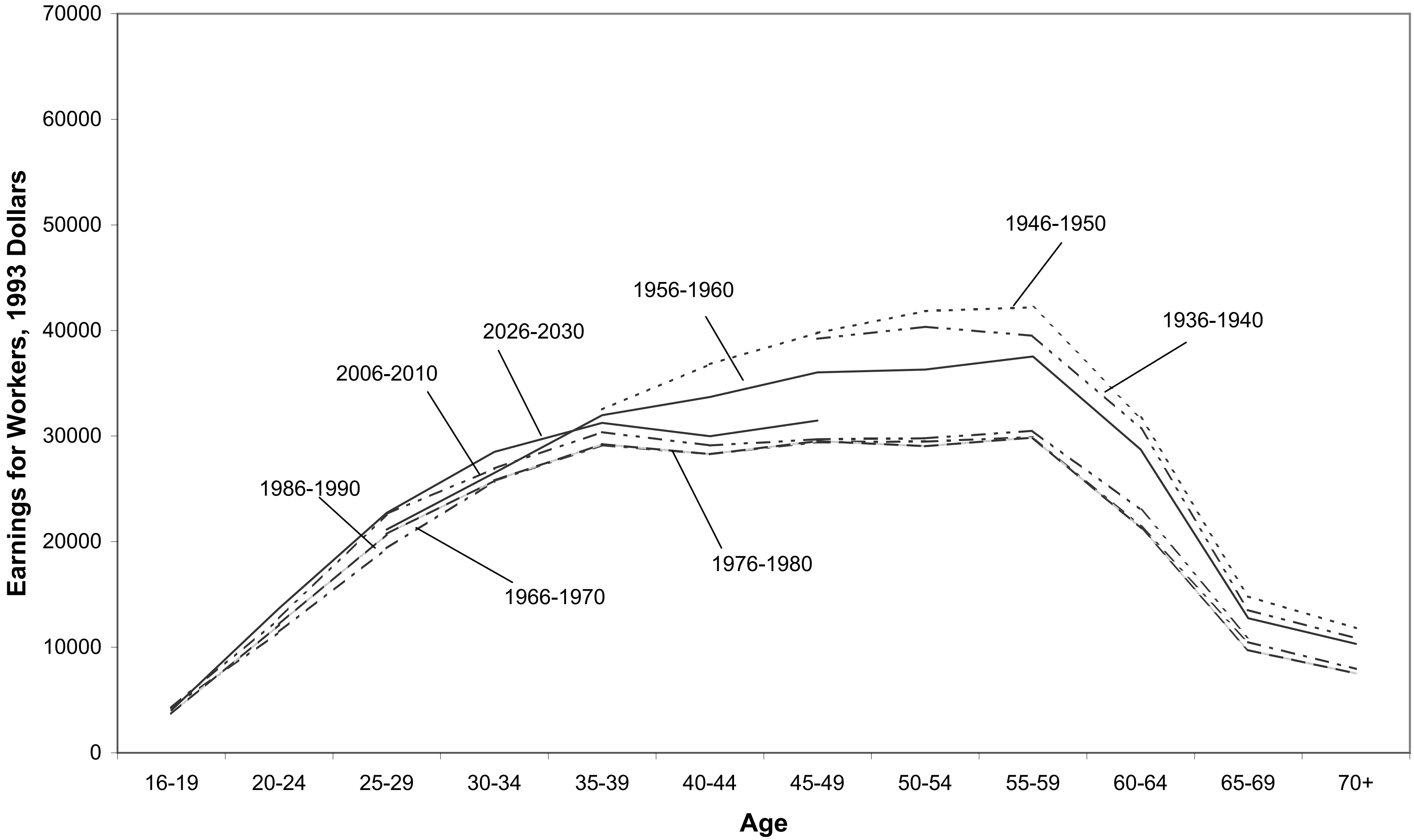

Figure 28. High-Educated Male Cohort Mean Earnings, CWHS Historical and Projected

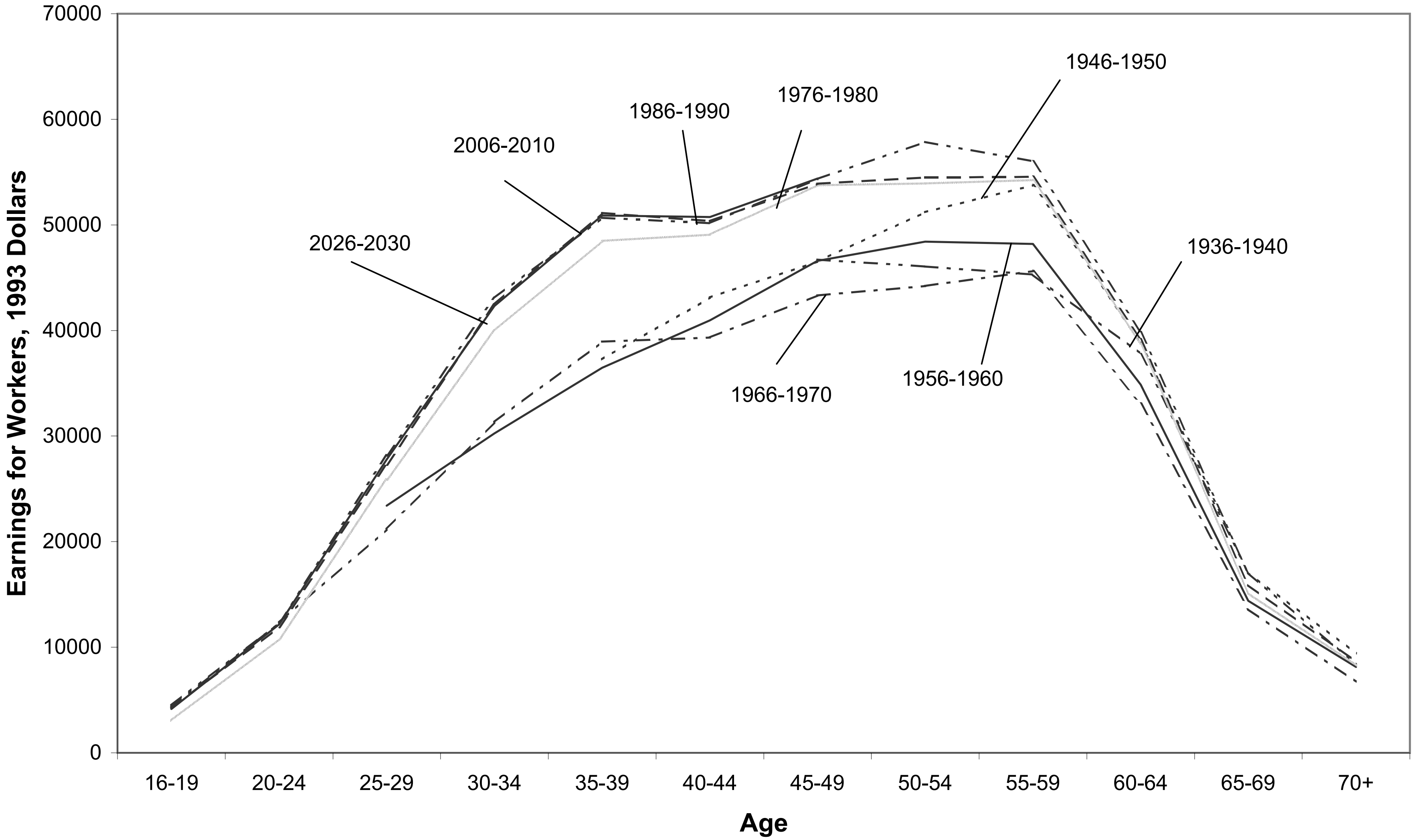

Figure 29. Low-Educated Female Cohort Mean Earnings, CWHS Historical and Projected

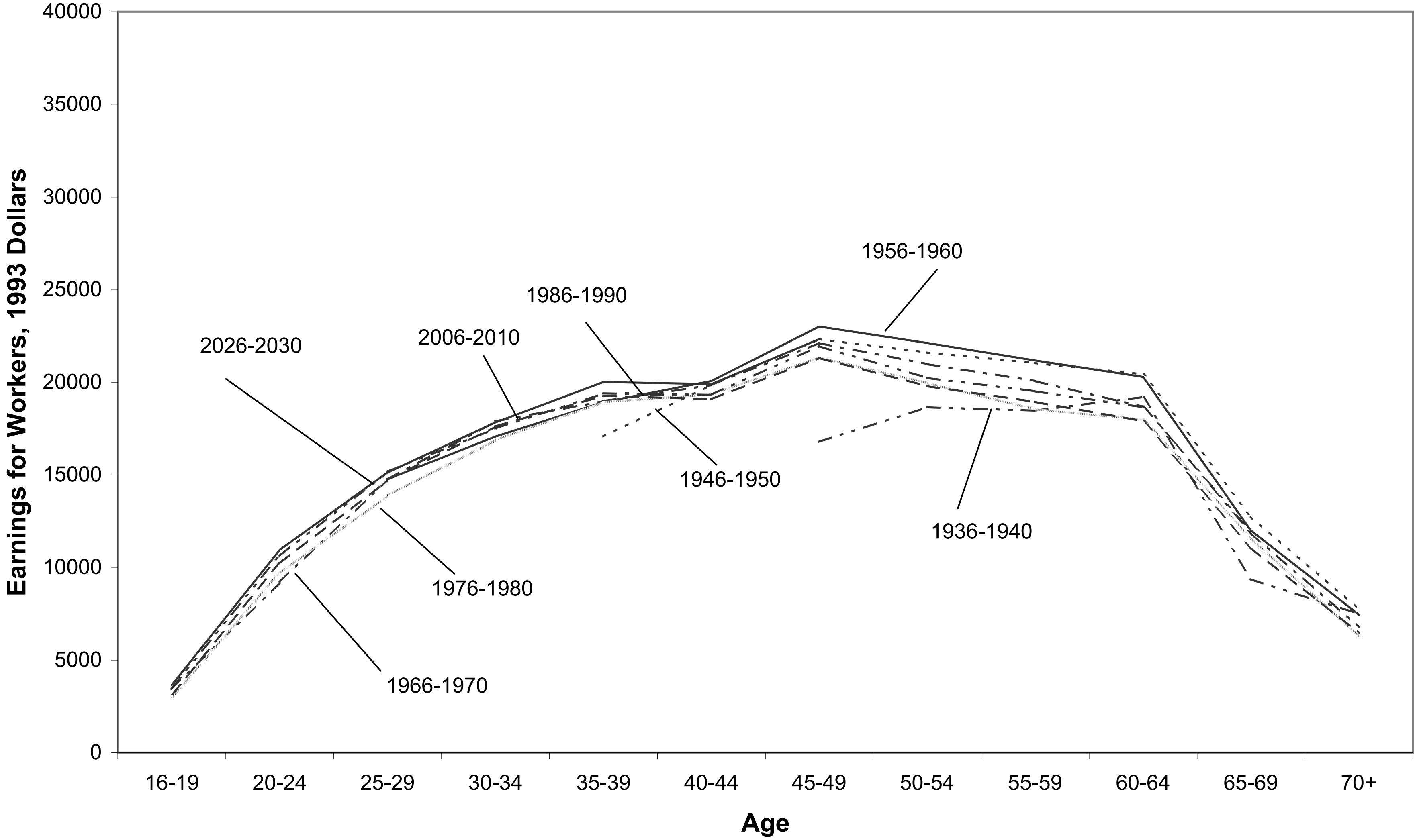

Figure 30. High-Educated Female Cohort Mean Earnings, CWHS Historical and Projected

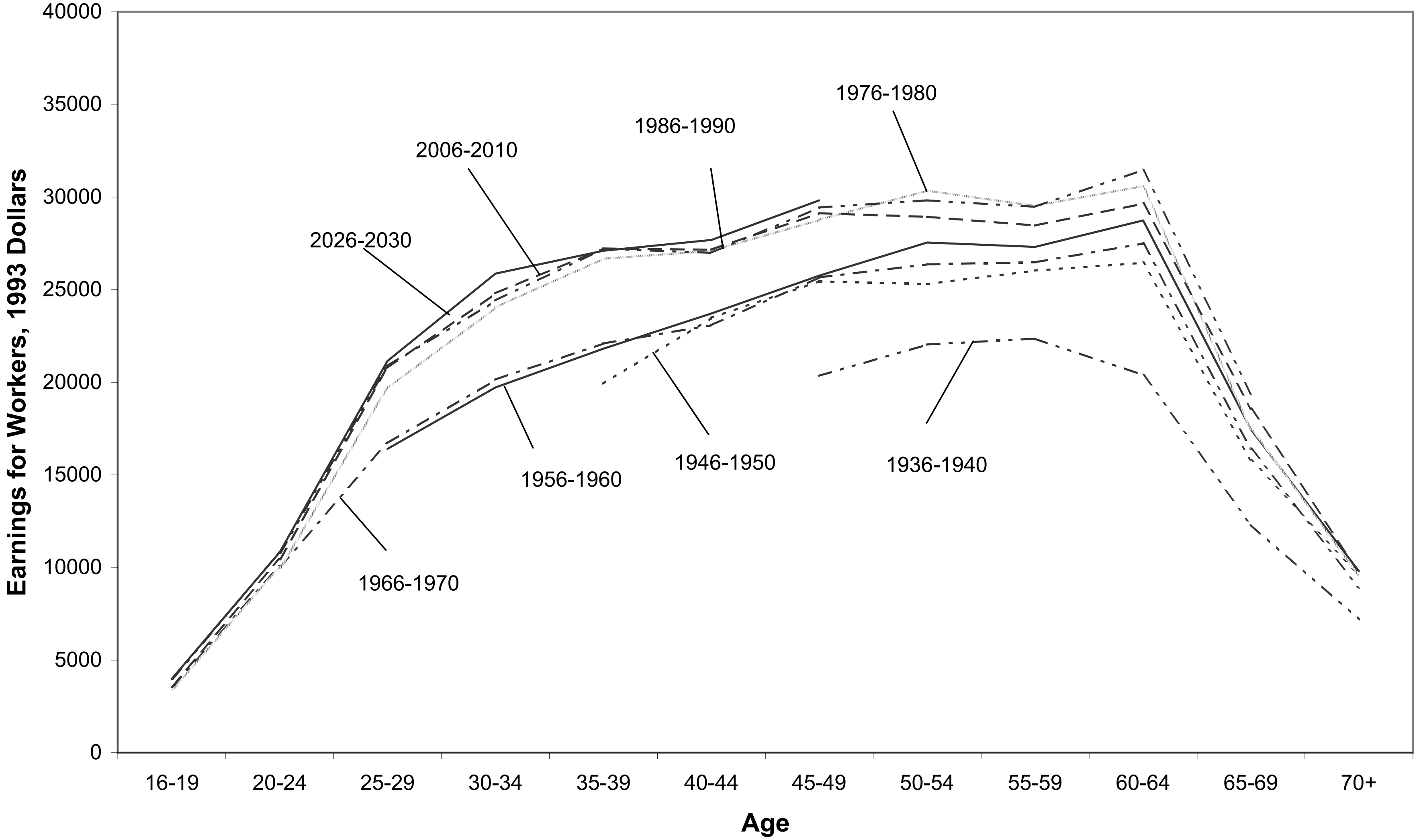

Figure 31. Lower Half of the Annual Earnings Distribution, Males and Females

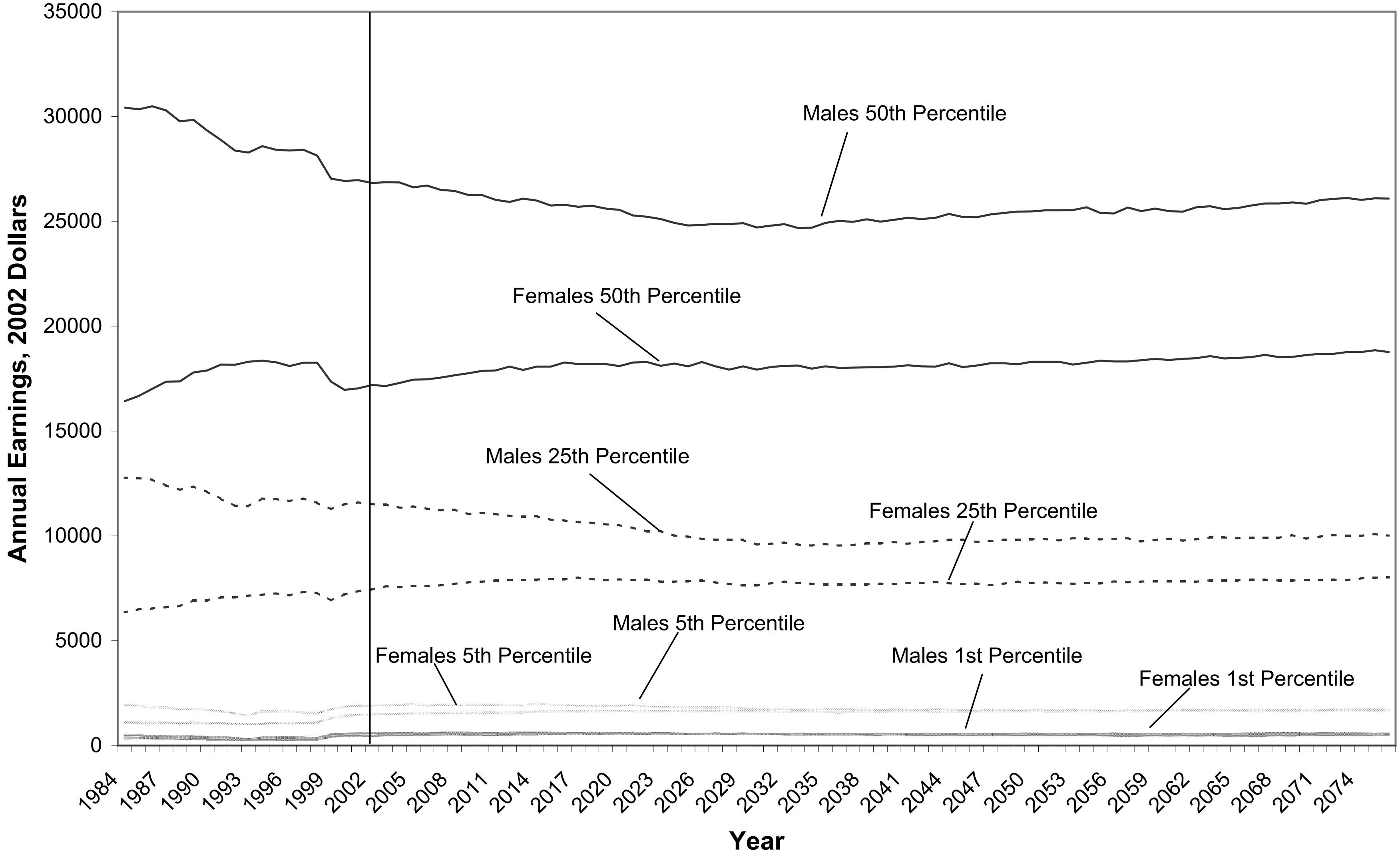

Figure 32. Top Half of the Annual Earnings Distribution, Males and Females

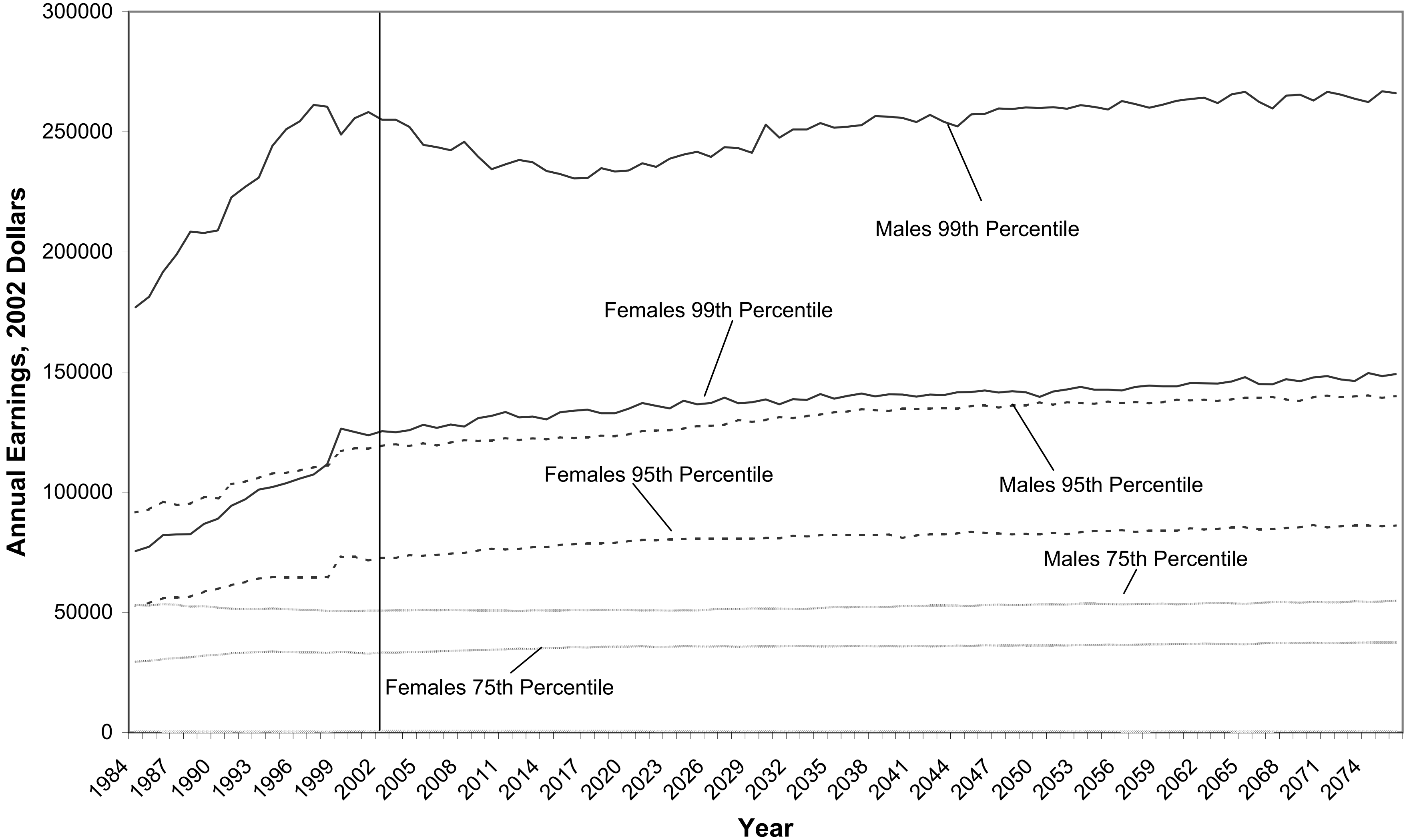

Table 10

Annual Earnings Distribution by Lifetime Earnings Decile, 50- to 60-Year-Old Males

Year		Lifetime Earnings Decile									
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1998	**1**	3.47	1.61	1.12	0.83	0.74	0.53	0.52	0.51	0.47	0.19
	2	2.86	2.24	1.40	0.93	0.74	0.50	0.42	0.47	0.31	0.15
	3	1.77	2.32	1.94	1.34	0.93	0.56	0.45	0.29	0.23	0.17
Annual	**4**	1.06	1.56	1.81	1.74	1.46	0.99	0.57	0.40	0.25	0.16
Earnings	**5**	0.37	1.01	1.53	1.86	1.65	1.56	0.93	0.56	0.41	0.13
Decile	**6**	0.18	0.68	1.02	1.37	1.80	2.02	1.46	0.91	0.36	0.20
	7	0.14	0.39	0.66	0.89	1.46	1.78	2.05	1.59	0.78	0.25
	8	0.07	0.15	0.35	0.72	0.70	1.27	1.94	2.37	1.94	0.52
	9	0.03	0.04	0.16	0.27	0.38	0.67	1.31	2.05	3.20	1.87
	10	0.02	0.02	0.03	0.05	0.14	0.14	0.35	0.85	2.06	6.36
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
2010	**1**	4.70	2.36	1.20	0.88	0.40	0.25	0.12	0.06	0.01	0.00
	2	1.90	2.26	2.00	1.57	1.05	0.61	0.30	0.24	0.06	0.02
	3	1.32	1.62	1.67	1.73	1.35	1.00	0.63	0.47	0.17	0.04
Annual	**4**	0.77	1.26	1.60	1.46	1.59	1.36	0.99	0.59	0.31	0.08
Earnings	**5**	0.52	0.88	1.19	1.31	1.41	1.52	1.46	0.95	0.61	0.14
Decile	**6**	0.32	0.59	0.89	1.02	1.55	1.51	1.57	1.37	0.91	0.27
	7	0.25	0.48	0.59	0.80	1.03	1.58	1.64	1.64	1.46	0.54
	8	0.12	0.35	0.44	0.64	0.92	1.09	1.61	1.85	1.94	1.03
	9	0.06	0.12	0.34	0.45	0.55	0.77	1.21	1.90	2.51	2.09
	10	0.03	0.06	0.08	0.15	0.15	0.30	0.47	0.94	2.01	5.79
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
2040	**1**	7.07	1.97	0.63	0.16	0.10	0.05	0.01	0.01	0.00	0.00
	2	1.70	3.76	2.17	1.24	0.60	0.30	0.14	0.06	0.01	0.01
	3	0.52	2.19	2.49	1.96	1.30	0.85	0.38	0.24	0.07	0.01
Annual	**4**	0.32	1.07	2.10	2.24	1.75	1.19	0.72	0.38	0.19	0.04
Earnings	**5**	0.13	0.49	1.25	1.81	2.05	1.79	1.22	0.88	0.33	0.04
Decile	**6**	0.10	0.26	0.77	1.31	1.81	1.83	1.76	1.29	0.73	0.15
	7	0.07	0.12	0.39	0.76	1.33	1.90	2.03	1.76	1.25	0.38
	8	0.05	0.07	0.10	0.36	0.71	1.32	2.03	2.33	2.08	0.95
	9	0.02	0.04	0.10	0.16	0.29	0.64	1.33	2.16	3.06	2.20
	10	0.01	0.01	0.02	0.02	0.05	0.13	0.36	0.88	2.30	6.23
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
2070	**1**	7.06	1.99	0.61	0.16	0.10	0.04	0.02	0.00	0.00	0.00
	2	1.69	3.65	2.38	1.06	0.63	0.36	0.18	0.03	0.04	0.00
	3	0.47	2.14	2.46	2.09	1.37	0.77	0.49	0.15	0.06	0.00
Annual	**4**	0.24	1.13	1.95	2.24	1.83	1.23	0.83	0.35	0.16	0.03
Earnings	**5**	0.21	0.56	1.31	1.89	1.86	1.64	1.26	0.93	0.26	0.08
Decile	**6**	0.12	0.29	0.65	1.29	1.78	1.96	1.72	1.33	0.65	0.18
	7	0.06	0.16	0.40	0.79	1.29	1.78	1.99	1.90	1.29	0.36
	8	0.08	0.04	0.16	0.32	0.81	1.39	1.94	2.24	2.16	0.86
	9	0.05	0.03	0.06	0.12	0.29	0.67	1.25	2.26	3.06	2.18
	10	0.00	0.01	0.03	0.03	0.04	0.14	0.31	0.80	2.32	6.31

Table 11

Annual Earnings Distribution by Lifetime Earnings Decile, 50- to 60-Year-Old Females

Year		Lifetime Earnings Decile									
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1998	**1**	3.46	1.96	1.16	1.02	0.67	0.52	0.35	0.26	0.24	0.35
	2	2.99	2.20	1.53	0.85	0.86	0.50	0.40	0.20	0.25	0.22
	3	1.81	2.21	1.87	1.35	0.85	0.72	0.45	0.31	0.21	0.22
Annual	**4**	1.04	1.71	1.82	1.69	1.35	0.93	0.65	0.43	0.24	0.12
Earnings	**5**	0.40	0.97	1.60	1.75	1.75	1.41	1.05	0.57	0.37	0.17
Decile	**6**	0.17	0.47	1.07	1.52	1.65	1.68	1.50	1.12	0.57	0.24
	7	0.06	0.27	0.46	1.01	1.49	1.83	1.76	1.66	1.07	0.36
	8	0.06	0.10	0.32	0.51	0.88	1.32	1.96	2.20	1.98	0.71
	9	0.00	0.06	0.07	0.19	0.37	0.92	1.31	2.00	2.94	2.11
	10	0.02	0.02	0.11	0.11	0.13	0.16	0.59	1.22	2.15	5.51
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
2010	**1**	4.59	1.94	1.29	0.83	0.67	0.32	0.22	0.05	0.04	0.03
	2	1.86	2.06	1.64	1.29	1.12	0.74	0.67	0.36	0.21	0.07
	3	1.08	1.46	1.61	1.34	1.16	1.17	0.94	0.68	0.42	0.16
Annual	**4**	0.73	1.37	1.31	1.33	1.26	1.10	1.06	0.82	0.67	0.34
Earnings	**5**	0.54	1.04	1.17	1.28	1.20	1.25	1.14	1.04	0.87	0.48
Decile	**6**	0.45	0.78	0.88	1.13	1.20	1.33	1.24	1.34	1.00	0.61
	7	0.30	0.51	0.76	0.96	1.07	1.38	1.42	1.41	1.37	0.84
	8	0.25	0.44	0.58	0.86	1.07	1.18	1.30	1.57	1.67	1.09
	9	0.15	0.26	0.49	0.61	0.83	0.93	1.29	1.59	1.84	1.99
	10	0.03	0.14	0.26	0.36	0.42	0.61	0.73	1.13	1.91	4.39
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
2040	**1**	6.57	2.23	0.69	0.27	0.13	0.05	0.05	0.01	0.01	0.00
	2	1.70	3.00	2.00	1.32	0.88	0.53	0.34	0.16	0.06	0.01
	3	0.77	1.87	1.98	1.43	1.40	0.98	0.71	0.51	0.26	0.09
Annual	**4**	0.40	1.11	1.55	1.70	1.62	1.11	0.97	0.84	0.51	0.19
Earnings	**5**	0.12	0.85	1.29	1.63	1.40	1.45	1.12	1.02	0.82	0.30
Decile	**6**	0.13	0.38	1.03	1.37	1.42	1.52	1.52	1.20	0.89	0.52
	7	0.14	0.26	0.68	1.00	1.23	1.49	1.47	1.53	1.40	0.84
	8	0.11	0.11	0.47	0.77	0.98	1.40	1.63	1.67	1.64	1.23
	9	0.04	0.13	0.26	0.39	0.66	1.10	1.47	1.74	2.16	2.05
	10	0.03	0.05	0.06	0.14	0.27	0.36	0.73	1.33	2.25	4.78
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
2070	**1**	6.46	2.33	0.71	0.28	0.12	0.02	0.02	0.00	0.00	0.00
	2	1.83	2.85	2.00	1.31	0.96	0.47	0.35	0.19	0.06	0.00
	3	0.65	2.04	1.93	1.63	1.25	0.99	0.66	0.52	0.30	0.04
Annual	**4**	0.33	1.08	1.81	1.54	1.37	1.29	0.98	0.90	0.52	0.16
Earnings	**5**	0.20	0.73	1.18	1.63	1.58	1.42	1.31	0.97	0.66	0.31
Decile	**6**	0.19	0.42	0.94	1.38	1.48	1.45	1.26	1.24	0.99	0.64
	7	0.15	0.21	0.66	1.02	1.24	1.54	1.66	1.44	1.29	0.78
	8	0.09	0.17	0.42	0.62	0.98	1.37	1.60	1.69	1.74	1.33
	9	0.05	0.10	0.27	0.43	0.78	0.96	1.46	1.81	2.16	1.96
	10	0.02	0.07	0.08	0.15	0.23	0.48	0.69	1.24	2.26	4.78

Figure 33. Average Earnings Variation over Ages 16-59 for 60-Year-Olds