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PROJECTING LONGITUDINAL MARRIAGE PATTERNS FOR LONG-RUN POLICY ANALYSIS

Josh O'Harra (e-mail: josho@cbo.gov)
John Sabelhaus (e-mail: johnsa@cbo.gov)
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I. Introduction

Imagine a longitudinal micro data file that contains individual earnings along with basic demographic variables such as age, sex, education, marital status, and spouse's characteristics 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 longitudinal 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 described above. This paper describes one set of building blocks in dynamic micro-simulation: marital transition equations that predict first marriage, divorce, and remarriage for individuals over time.

A dynamic micro-simulation model starts with economic and demographic data for a current sample of the population and then stochastically "ages" that sample forward through time, ultimately generating a longitudinal data file, which is useful for studying Social Security and other programs under various policy rules. The stochastic simulation process involves applying a sequence of "transition equations" to each person in the sample. Those transition equations are, in effect, probability distributions for demographic events (such as marital transitions, educational attainment, or even death) and economic events (such as changes in earnings or pension coverage). Random numbers are compared with estimated transition probabilities to determine actual outcomes and thus preserve underlying heterogeneity in the population.

Projecting marital transitions (first marriage, divorce, and remarriage) is an integral part of dynamic micro-simulation, because marriage histories directly affect beneficiary status and benefit amounts under many government programs and because marital status influences labor supply, saving, and other types of relevant behaviors. However, there are several ways to interpret the existing data on marital transitions, and the interpretation chosen may affect one's long-run projections of marital outcomes.

The first half of this paper considers historical patterns of marriage and divorce using the retrospective marital history module in the 1996 Survey of Income and Program Participation (SIPP). The SIPP data show significant effects on transition probabilities from some expected variables, such as age, education, and income (for all marital transitions), and nonlinear duration effects (for divorce and remarriage). The data also indicate some dramatic differences across cohorts even after controlling for age, education, income, and duration; thus, dynamic micro-projections require choosing out-of-sample values for those cohort effects. For example, people born in the 1960s and 1970s are less likely to get married at younger ages (even after controlling for education and other variables) than people born in the 1950s or earlier. Therefore, making projections for future generations requires speculating whether first marriage probabilities for people born in the 1980s and beyond will be the same, lower, or possibly even higher than those for the 1960s and 1970s cohorts.

The second half of this paper uses those estimated marital transition equations to show how longitudinal marriage patterns might be projected through 2075 for a sample of the U.S. population. Given this technique and the underlying assumptions it implies, aggregate results from the dynamic micro-simulation modeling are fundamentally consistent with projections generated by standard actuarial techniques. These results generally suggest that fewer people are ever marrying, divorce rates are relatively flat, and remarriage rates are declining. Furthermore, they imply that the mean age of first marriage will creep up over the period, leveling off around age 28.

The effect of those trends on future cohorts suggests that the percentage of nonwidowed women eligible to collect benefits on a spouse's earnings record will fall. If the past relationship between income and marital behavior continues to hold, this trend will probably affect low-earning women more adversely than it will affect high-earning women. These projections illustrate the capabilities of one set of modeling techniques. As with any forecast, the results depend on assumptions about future trends in behavior; undoubtedly, other assumptions would produce different results.

Because Social Security's Old-Age and Survivors Insurance benefits represent the single largest government transfer program, with future obligations expected to increase substantially as the baby-boom generation begins to retire, detailed longitudinal earnings and marital projections represent a valuable tool for long-range policy analysis. There are two ways to collect OAI benefits. Most OAI beneficiaries draw an award based on their own earnings record (so-called fully insured workers). Individuals who are not fully insured workers but who are or were married to a fully insured worker can receive OAI benefits based on the earnings records of their spouse. Those people must either be currently married to a fully insured worker, a widow(er) of a fully insured worker, or an ex-spouse of a fully insured worker with a marital duration of 10 or more years.[1] It is also possible for an individual to be dually entitled--that is, to receive a combination of own-worker benefits and some type of spousal benefits.

In addition to their significance with respect to explicit benefit rules, marital histories affect other behavior relevant to forecasting Social Security obligations. For example, marital status affects labor supply. The theory is that the presence of a second income may dictate

1. At Social Security's inception, divorced spouses were not eligible for benefits on their ex-spouses' earnings records. In 1965, divorced spouses with 20 or more years of marriage to a fully insured worker became eligible for benefits; the threshold was lowered to 10 years in 1977.

whether both partners need to work. That decision, in turn, affects the number of retirees claiming benefits based on their own earnings history. Retirement timing decisions are also partly determined by marital status. Workers who do not have a spouse or family reliant upon their wages could be more likely to exit the labor force earlier than those with family obligations. Married couples are also likely to have higher personal savings. Finally, the well-documented relationship between marriage and mortality suggests that changes in marital patterns may operate on Social Security's finances by changing the annuitized value of OAI benefits at retirement. That is, if more people enter retirement unmarried, their life expectancy will be shorter, on average, and the annuitized value of their benefits will be smaller.

The multiple interactions between marital status and other determinants of Social Security's finances make it necessary to model each process explicitly. Actuarial methods treat the age/sex/marital status group as the relevant unit of analysis. Those estimates generate reasonable cross-sectional marital distributions but fail to account for the timing of transitions and the characteristics of people experiencing them.[2] The alternative method--dynamic micro-simulation--allows for interaction between covariates and reflects true population heterogeneity.

2. See Frees (1999) and Bell (1997).

II. Marital Transitions Across Age and Cohort Groups

Marriage patterns in the United States have changed in fundamental ways during the past several decades, and the interpretation of those changes will dominate future projections. For example, rates of first marriage at the youngest age groups have fallen significantly for cohorts born after 1950, but has that trend stopped? Also, has the observed increase in divorce probabilities for cohorts born after 1950 slowed or even reversed? This section of the paper uses data from the 1996 Survey of Income and Program Participation retrospective marital history module to analyze marital transitions across age and cohort groups. The SIPP data confirm observations about marital transitions that are evident in aggregate data.

Although the SIPP is a large and nationally representative sample of the population, there are still reasons for caution when using its data to analyze marital transitions, especially over time. Table 1 compares SIPP marital transition rates with aggregate data from the Vital Statistics database collected by the National Center for Health Statistics (NCHS).[3] In general, the aggregate transition rates in the data sets are similar; noticeable differences between the 1990 and 1995 measures include lower divorce rates for both sexes and a lower remarriage rate for men. Those differences can be explained by the slightly different time periods, the fact that the SIPP data exclude the institutional population, and reporting problems associated with distinctions between (for example) divorce and separation. The table does not compare SIPP and NCHS marital transitions for earlier time periods because the SIPP, by construction, only questioned

3. The NCHS data is the main data set used by the Social Security Administration in its actuarial analysis of marital transitions. See, for example, Bell (1997). The data were compiled annually from state Vital Statistics offices and issued in numerous public-use formats. However, as a result of budget cuts in 1990, those data are no longer collected or reported.

people alive in 1996 about their marital history. Therefore, any comparison of earlier time periods would not be meaningful, but it should be acknowledged that recall bias might affect the analysis that follows.

Figures 1 through 8 show estimated marital transition probabilities from the SIPP across age and cohort groups. The graphs are produced using a kernel-smoothing technique, where any point on the graph is a weighted average of all observations within a fixed "band" around that age.[4] For example, the value for age 25 in a given cohort is actually a weighted average of people ages 23, 24, 25, 26, and 27 in that cohort, with people age 25 having the highest weight, people ages 24 and 26 having smaller weights, and people ages 23 and 27 having even smaller weights. All of the vertical axes are expressed as rates per 100 eligible, where eligibility varies with the transition--first marriage eligibles have never married, divorce eligibles are currently married, and remarriage eligibles are currently divorced or widowed.

First marriage rates are shown in Figures 1 through 4. Figures 1 and 2 show annual rates of first marriage, while Figures 3 and 4 show cumulative rates. (One-hundred minus the cumulative rate at any given age is the fraction of people who never marry.) The two sets of figures tell a similar story in slightly different ways. There have been significant declines in rates of first marriage at young ages (through the mid-20s) for all cohorts since the 1950s. However, the *rate* of decline (the gap between the sequentially ordered cohort probabilities at a given age) for both men and women seems to have slowed. Also, there is some evidence that rates of first marriage may actually be slightly higher at older ages (late 20s and beyond) for more recent

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4. Although the 1996 SIPP has over 69,000 observations eligible for the marital history module, straight tabulation by age, sex, and cohort would still generate noisy graphs because of the low rates of occurrence for marital events.

cohorts. Thus, as noted, there is no single statement about time/cohort effects that describes what is happening at all ages, which suggests flexibility in the econometric specification for the transition equations. The one distinguishing feature for both men and women is the existence of the hump-shaped annual probability distribution by age, but the exact shape has evolved over time.

Figures 3 and 4 show rates of first marriage in a slightly different way, as a cumulative probability from age 16 onward. Men and women born in more recent cohorts are less likely to have ever been married by that age. However, the fact that the gaps between cohorts shrink with age is consistent with the slight increases in marriage rates at older ages. More important, this fact implies that applying the same marriage rates to a larger (as yet unmarried) population will eventually asymptote to similar cumulative levels.

Figures 5 and 6 show divorce rates by age and cohort for females and males, respectively. For both sexes, divorce rates for cohorts born after 1950 are noticeably higher at younger ages, but those rates are approaching (or even below) the pre-1950 cohort levels in the latest years for which the SIPP data are available. There is also some evidence that divorce rates for some age groups in the 1960s cohort (25- to 35-year-olds) are actually lower than those of the 1950s cohort, signifying a reversal back toward the pre-1950 cohort rates.

The remarriage rates in Figures 7 and 8 indicate less change across cohorts than the rates for first marriage and divorce. There seems to be little, if any, difference in the rates of remarriage for women over time, and only a slight decline (but proportional across age groups for the observed cohorts) for men. As with the other transitions, there is a smooth declining pattern in remarriage probabilities by age.

The important forecasting question with respect to all three sets of marital transitions is whether the observed differences across cohort groups can be explained empirically. For example, as will be shown, the micro data indicate that whether or not a person attends college affects his or her probability of first marriage, and it is well known that college attendance rates have risen over time. But, is the increase in college attendance (or any other reasonable explanatory variable one might enter into a transition equation) enough to explain the changes in first marriage rates across cohorts as shown in Figures 1 through 4? That issue is addressed in the next section.

III. Modeling Marital Transitions

The 1996 SIPP data used to generate Figures 1 through 8 indicate key aspects about marriage and divorce rates that should be considered when estimating marital transition equations: there are smooth but generally nonlinear patterns of transition probabilities across age groups *within any given cohort*, and there seem to have been changes in transition rates *at certain ages* across cohorts. It remains to be shown in this section whether those observations can be explained by underlying determinants of marital transition, such as education and income (for all transitions) or duration in state (for divorce and remarriage). But it is clear that flexibility in the econometric analysis 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 some transition probabilities have actually moved in different directions along the age dimension.

It is useful to begin this section by considering the possible determinants of marital transitions and existing empirical evidence about their effects. The three transitions considered here are first marriage, divorce, and remarriage.[5] Theory suggests that first marriage is influenced by factors such as age, sex, race, educational attainment, income, the presence or absence of children, urbanicity, possibly some parental characteristics, and some version of a time or cohort effect.[6] Divorce determinants are basically the same but also include the number of previous marriages and marital duration. Finally, the factors affecting remarriage are similar to those affecting divorce, except the duration variable is time since divorce and an additional control can be added to account for the method of marital termination (divorce or death). Also, those processes can be modeled at the couple level so that the effect of a spouse's characteristics could also be estimated (for example, the effect of a husband's and wife's income differential on the probability of marital dissolution).

There is some variation in the actual variables used and methods employed in dynamic micro-simulation models because of differences in underlying data sources and differences in the list of control variables available in the model. The Social Security Administration's POLISIM (a spin-off of the CORSIM model) considers first marriage as a logistic process estimated separately on 20 demographic groups.[7] The sample breaks are by age, sex, race, education, and weeks worked. Divorce is modeled for four groups as a function of marital duration, race and, since POLISIM uses linked data, spouse wage differentials. Finally, POLISIM models remarriage as a

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5. Widowhood is a function of spouse mortality probabilities and is considered separately in the dynamic micro-simulation model.

6. This list is compiled based on Lillard and Panis (1999), Perese (1999), Peters (1988), and Lillard and Waite (2000).

7. Caldwell and others (1998).

two-step process. First, logits are used to determine who from different age/sex/racial groups reenters the marriage market and, from there, actual spouses are assigned. POLISIM does not control for time trends or cohort effects in any of the transition equations.

The Urban Institute's DYNASIM model uses a similar approach. Its sample relies on different data but employs similar sample breaks.[8] There are eight logits estimating first marriage probabilities for various age/sex groups that rely on standard social and economic characteristics of individuals. Divorce probabilities are generated in a similar fashion, but they rely on the estimation of a single equation and the use of couples as the relevant unit of observation. Remarriage is randomly assigned on the basis of age-specific remarriage rates from the 1990 Vital Statistics. Again, while the recent trends in marital phenomena are considered in determining the relevant sample, in no case does DYNASIM explicitly account for time or cohort effects.

A final example is the micro-simulation model used by the Social Security Administration to project policy outcomes for the next 20 years: the Modeling Income in the Near Term (MINT) project. The MINT model uses only two hazard models, one for divorce and one for any marriage.[9] Although that model employs a different functional form (a hazard model), the determinants of marital transitions are standard: age, sex, race, educational attainment, number of previous marriages, and income. Finally, unlike the previous two models, MINT explicitly controls for time. With respect to marriage, calendar time (1901-1994) is used; for divorce, calendar time, with a node at 1980, is employed. For both transitions, that time trend is extended by multiplying the coefficient estimate by the calendar year. Consequently, the effect of time

8. Perese (1999).

9. Lillard and Panis (1999).

continues to grow.

The marital transitions considered here, as in the models above, are limited by both the data set used for estimation and by the list of control variables available in the micro-simulation model itself. The SIPP data set has detailed demographics such that any variable listed above is a potential candidate for use in the equations, but the fact that (for example) race is not available on the data set used for the Congressional Budget Office's micro-simulation model implies that it would not be meaningful to control for race in the SIPP-based estimation. In general, when using the SIPP one only has access to current income information. But the estimation here relied on a special version of the SIPP that has been linked to SSA's administrative earnings data, so it can use earnings for the entire longitudinal history of sample members. Furthermore, the marital history topical module allowed for the creation of longitudinal marital histories. When combined, those data allowed for person-year units of observation and a final set of controls that considered age, sex, education, lagged income, and time/cohort effects (for all three transitions) and a nonlinear function of duration (for divorce and remarriage).

Given the list of control variables, the next decision involves choosing an estimation strategy. Most of the exercises above involve splitting the sample by demographics and estimating either logit or hazard models. Although it is clear that one should estimate different equations across sex groups, the impression of the data one gets from Figures 1 through 8 is that broad age groups will not capture the interesting curvature of the underlying transition probabilities across age groups. Also, it is apparent that cohort/time effects will vary with age, and it is also likely that the effect of some control variables (education or income) will vary across age groups. So, even if one used a polynomial in age to capture the curvature of the transition probabilities by age, the equation would still be imposing the same effect from the other control variables by age. As indicated in the last section, these observations motivate a very flexible approach to measuring determinants of transition probabilities.

The econometric approach used here can be thought of as an "age-centered" estimation technique, which is an extension of the group-based approach used by other models. A separate transition equation is estimated for each single year of age and each sex group, but the sample used in the estimation actually includes every observation within a fixed age band around that point. For example, the estimation for males age 25 actually includes all males ages 21 though 29, though, as in the development of the smoothed Figures 1 through 8, the observations farther from the center are weighted less heavily. 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 (income, education, duration, 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 be the case if one ran single equations for each individual age).

The concerns about using an overly restrictive estimation strategy for the three marital transitions are borne out in the results, which are shown in Tables 2 through 7. Each table shows a series of logits estimated for a given sex group; for example, Table 2 has the results of estimating separate first marriage logits for females ages 17 through 60.[10] Each set of estimated coefficients is reported on a separate row, with significant (90 percent level) variables indicated by

10. The "bands" actually vary in size at the youngest ages; the equation for 17-year-olds includes ages 16 through 19, for 18-year-olds includes ages 16 through 20, etc; for most ages the bands are set to plus or minus four years.

BOLD numbering. As indicated, 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 age.

The predominance of **BOLD** numbering in Tables 2 and 3, especially at the youngest ages, implies that the chosen correlates do in fact significantly affect first marriage probabilities. For both men and women, education (a dummy variable indicating 14 or more years of schooling) has a significant negative effect on first marriage through the early 20s but then becomes positive and significant for age groups through the mid- to late 30s. Income (which is lagged, not contemporaneous) has a significant positive effect for both women and men at most ages, though the effect turns negative (and eventually becomes significant) for women past their late 40s.

Tables 2 and 3 also provide an answer to one of the questions posed above: do the other control variables (education and income) explain the trends in first marriage rates across cohorts as shown in Figures 1 and 2? The answer is clearly no, as the residual cohort effects are all significantly negative for the youngest age groups. But, as expected, that effect diminishes with age, as the first marriage probabilities converge for the older age groups (and, as noted, might even be higher for the more recent female cohorts at older ages). The obvious question for forward-looking micro-simulation is how to fill in cohort effects after the historical data ends--that is, for ages 46 and above for the 1950s cohort, ages 36 and above for the 1960s cohort, and ages 26 and above for the 1970s cohort.[11] This paper explores one of several possible approaches.

When considering how to extend the cohort effects, it helps to show the patterns in a graphical form. The solid lines in Figures 9 and 10 show the residual cohort effects for first marriage (from Tables 2 and 3) by age for the 1950s, 1960s, and 1970s cohorts. The dotted lines show the extensions applied to the cohort residuals in order to produce forecasts. Notice first that the last observed cohort residual for both males and females (the age 45 value for the 1950s cohort) is assigned to all older age groups for that cohort. This is consistent with the following interpretation: women (men) in the 1950s cohort were slightly more (slightly less) likely to get married at age 45 than previous cohorts, and thus it seems reasonable to expect that the same will be true at ages 46 and above.

The second set of observations applies to the values for the 1960s and 1970s cohorts between the ages of 26 and 46. The "s-shaped" pattern of estimated residuals is consistent with the shifting of the peak age of first marriage rates to the right over time at the same time the height of the peak is falling (see Figures 1 and 2). By assigning a pattern of residual cohort terms that is proportionally shifted from the previous cohort, the extensions shown in Figures 9 and 10 keep the shape of the probability distribution constant but continue the shift. Thus, there is a smooth transition of first marriage probabilities at all ages across the three cohorts. The convergence of cohort effects at older ages is consistent with the underlying convergence of the first marriage rates, again, as indicated by the available data in Figures 1 and 2.

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11. The SIPP data did not suggest any basis for extending trends to the 1980s cohort and beyond, so the last set of residual cohort effects derived in all cases is for the 1970s group. Those residual terms are then applied to the 1980s cohort and all future cohorts "born" into the model.

Tables 4 and 5 show age-centered logit estimates for divorce rates of women and men, respectively; again, the importance of flexibility is underscored by the results. Education has mixed (but generally negative) effects on divorce, and income actually has different signs for the two sexes: lower lagged income is more likely to lead to divorce for men but less likely to lead to divorce for women. The divorce equations also show a nonlinear specification in marital duration; the positive or insignificant linear term and negative squared term for many age groups are consistent with underlying divorce patterns: the probability of divorce initially rises after couples are married but eventually starts to fall after they have been married a certain number of years (though again, the data indicate that this nonlinear effect itself varies with age).

Strong residual cohort effects are as evident for divorce as they are for first marriage, but here the data may actually offer a little guidance about how to extend the residuals. The residual cohort-dummy coefficient estimates in Tables 4 and 5 (also shown in Figures 11 and 12) clearly reflect the patterns in the overall divorce probabilities by age and cohort (Figures 5 and 6). Divorce rates are higher for both sexes at younger ages in the 1950s and 1960s cohorts, but that effect disappears with age--there are no significant residual differences in divorce probabilities for the two younger cohorts at the latest ages that can be observed. Thus, one could speculate that divorce rates will match those for the pre-1950 cohorts at older ages.[12]

The two sets of remarriage equations also confirm the importance of education, income, and duration as underlying determinants, but residual cohort effects seem smaller (again, as suggested by Figures 7 and 8). Tables 6 and 7 show the estimated coefficients; education has mixed effects across age and sex groups, while income is generally a positive predictor of

12. This is consistent with SSA's assumption of an unchanging central (age-adjusted) divorce rate during recent years and for the 75-year forecast horizon.

remarriage. One also observes the same stable nonlinear duration effects as probability of remarriage initially rises after a breakup, then begins to fall. The residual cohort terms are generally smaller and often insignificant, reflecting the similarity of the remarriage rates by cohort and age shown in Figures 13 and 14. To the extent that there are patterns (slightly lower remarriage rates at all ages), it seems reasonable to extend those forward in time.

The dramatic changes in marital transition rates indicated by the SIPP data across age, sex, and cohort groups cannot be explained away by underlying economic variables or changes in educational attainment. Further, the changes are not easily captured by time trends, because the changes in transition rates often go in different directions at different ages, and even the trends that are in a given direction (for example, the drop in first marriage rates at young ages) seem to have changed slope, slowing in recent years. To make projections, one can do little more than speculate how those patterns will continue to unfurl for existing cohorts as they age and for future cohorts at all ages. The implications of the choices made for extending the residual terms are drawn out in the next section, which uses the estimated transition equations in a dynamic micro-simulation setting.

IV. Projecting Longitudinal Marriage Patterns: 2000-2075

The goal of this paper is to show how to generate a set of longitudinal marriage histories for a *future* sample of the population in a dynamic micro-simulation context. Given the structure described above, the inputs to projecting micro marriage patterns include a base micro data file with economic and demographic information for a current sample of the population; a set of marital transition equations for first marriage, divorce, and remarriage; and another set of transition equations that predicts the independent variables that affect marital transitions (in this case, income and education). This section describes how those pieces are brought together in the Congressional Budget Office Long Term (CBOLT) policy simulation model and provides some basic results of the marital projection over the 2000 to 2075 period.[13] The results depend on a variety of assumptions, including how transition probabilities will evolve in the future. The illustrative calculations presented here show the implication of just one set of assumptions.

The CBOLT project began as an actuarial ("cell based") model intended to mimic the Office of the Chief Actuary's (OCACT's) methods for predicting the finances of Old-Age, Survivors, and Disability Insurance (OASDI). The second version of the model built upon the standard actuarial capabilities and introduced stochastic (Monte Carlo) simulation as well as dynamic macro-feedback effects.[14] CBOLT is currently entering its third stage, in which a dynamic micro-simulation model embedded in the stochastic macro growth framework will replace the standard actuarial projection modules for OASDI tax and benefit outcomes. The marital equations developed in this paper are an integral part of that third phase of CBOLT

13. The labor force participation and earnings equations used in conjunction with these marital transition equations are discussed in Harris and Sabelhaus (2002).

14. For a more thorough discussion, see CBO (2001).

development.[15]

The base data set used for all CBOLT projections is the Continuous Work History Sample (CWHS). 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 3 million individuals with earnings reported for 1951 to 1998.[16] Each year, the entire sample is followed, recording taxable earnings, total compensation, self-employment status, OASDI 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, in which 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 with the available cross-section or public-use longitudinal files such as the Panel Survey of Income Dynamics (PSID). Available cross-section data sets do not have the requisite longitudinal histories needed to project forward using dynamic micro-simulation.[17] Publicly available longitudinal data sets like the PSID are much smaller than the CWHS, and those data also suffer from response problems for the highest-earning individuals as well as recall bias. The CWHS is an administrative sample and therefore has much better reporting of income for the entire earnings distribution. The downside is that the administrative nature of the CWHS limits the demographic

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15. The simulations presented here do not use the entirety of the CBOLT projection machinery. For example, some of the micro/macro linkages that will exist in the final model (marriage affects labor supply, which affects aggregate real wage growth; that, in turn, affects individual income, which feeds back into marital transitions) are ignored.

16. See Smith (1989).

17. 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.

data to the information that is available on the initial Social Security Number application: year of birth, sex, and race.[18]

Given the lack of detailed demographics, it is necessary to impute several key variables--such as educational attainment, marital status, and marital history--when using the CWHS to project future Social Security taxes and benefits. Those variables are imputed on the basis of measured correlations between CWHS-observable and the imputed variables in the PSID, the Survey of Income and Program Participation, and the Current Population Survey.[19] Additionally, part of the imputation strategy relies on historical simulation using CBOLT's own simulation modules over a period for which there are no actual micro data, but there are aggregate control totals with which simulation results can be compared.

The historical simulation exercise is a useful gauge of whether the estimated transition equations are doing a good job of predicting marital outcomes in recent history. The simulations start in 1984, at which point everyone alive in the CWHS has been assigned a marital status, education, and duration in the relevant marital state. The assignments are made such that the starting (1983) population matches the characteristics of the (SSA Area) population that CBOLT uses for its aggregate reference point. The simulation then proceeds forward for 1984 through 1998 using the actual CWHS earnings and estimated marital transition equations. The results of the exercise are a set of "calibration factors" that are, in effect, average errors in targeting the observed aggregate marital distributions (again, as reported in the SSA Area population estimates). Figures 15 and 16 illustrate the nature of the marital transition calibration factors (by

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18. 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.

19. A discussion of the methods and data used in the imputations is available upon request.

age) produced by the historical comparison. As hoped, there is little systematic divergence between the actual trends in marital status and the results of the micro marriage modules.[20]

The fact that the marital transition equations estimated here are able to capture the trends in aggregate marital distributions during the 1984 to 1998 period suggests that (setting aside uncertainty about how to extend the residual cohort terms) the model is capable of generating reasonable cross-sectional marital distributions. That conclusion is borne out in Table 8 for the entire population and in Figures 17 and 18 for people ages 62 to 67 for whom Social Security projections are particularly relevant.

Table 8 shows cross-sectional marital distributions over time in both the OCACT and CBOLT base-case projections. The most striking result is the similarity between the cross-sectional marital distributions over the 75-year period; closer inspection shows a few small but systematic differences.[21] For example, CBO's approach consistently produces fewer divorcees as a proportion of the population. Also, by the end of the projection period, CBO's estimates yield about the same percentage of never married females but a slightly higher fraction of never married males. The proportion widowed is slightly different, but that result stems from different mortality projections.

At first glance the fact that the proportion of the population that never married is decreasing while the proportion married is increasing might appear to contradict the earlier story

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20. The only noticeable errors from the perspective of simulating forward are for divorce; the SIPP data are too thin to completely capture the drop in divorce rates for younger cohorts that occurred in the 1980s and 1990s. These "calibration factors" for divorce effectively act as another set of cohort terms when projecting into the future.

21. The similarities are even more striking when one considers that some of the processes used to project forward are very different. For example, OCACT uses the distribution of "available" mates by age and sex to predict how many marriages will occur, while CBOLT does not. For a thorough discussion of the OCACT actuarial projections, see Bell (1997).

suggesting that fewer people are marrying. However, because the age composition of the population is changing, measures of overall cross-sectional distribution by marital status do not accurately reflect the trends in either the OCACT or CBOLT projections. Figures 17 and 18 isolate the trends in the cross-sectional marriage distribution for people ages 62 through 67. That age group is interesting because, by this point in their lives, most of the cumulative effects of all three transitions modeled in this paper will probably be evident. These graphs suggest that the age-centered transition equations, combined with the minor adjustment factors derived from the historical simulations, generate individual behaviors that (when added up) approximately match the aggregate projections used by the Social Security actuaries. Furthermore, these pictures support our hypothesis that the transition equations should generate a smooth transition to a new distribution of marital status outcomes.

The CBOLT marital transition equations seem capable of generating reasonable cross-sectional patterns, but what about longitudinal outcomes? In addition to classifying the right number of people as marrying, divorcing, and remarrying in any given year, it is important to ensure that these transitions occur at the appropriate points in an individual's life-cycle and that the distributions of the number of marriages and marital durations across cohorts are reasonable.

The first bit of evidence that the longitudinal properties are satisfactory comes from looking at mean age at first marriage, shown in Figure 19. The solid lines represent Vital Statistics data covering the period between 1964 and 1990. The CBOLT projections start in 1984 and extend through 2075, thus there is a six-year overlap in the graphs. Historically, the mean age at first marriage has been drifting upward, which is consistent with the cohort analysis presented in Figures 1 and 2. Between 1984 and 1990, the CBOLT historical simulation produced mean ages of first marriage very near those registered in the Vital Statistics. That similarity suggests that the model accurately predicts the timing of transitions into first marriage. While the trend of delaying first marriage is predicted to continue for some time, it eventually stabilizes at about age 28 for both sexes, because once the 1980s cohort is through the relevant ages there are (by assumption) no further cohort effects. Note that the average age differential between the sexes shrinks over time, which is consistent with the extended positive residual cohort term for female first marriage probabilities (and negative term for males).

The second observation on longitudinal outcomes comes from looking at the trend in marital duration at the time of divorce, as shown in Table 9. This statistic is particularly interesting to Social Security analysts because of the duration requirement that governs benefit eligibility for divorced spouses. The CBOLT transition equations suggest that the typical duration of those marriages ending is divorce is not necessarily expected to fall. Again, at first glance, this result may seem counterintuitive, because of increased divorce rates. This trend is, however, supported both by actual data and theoretical determinants of divorce. Vital Statistics reports a steady, albeit slight, increase in the duration of marriages ending in divorce. This increase suggests a smaller proportion of very short marriages. Divorce researchers have posited that as marriage ages drift upward and cohabitation rates increase, the number of weak, official marriages will decline.[22]

There are ultimately many ways to tabulate longitudinal marriage outcomes in a dynamic micro-simulation context and thus draw conclusions about the model's properties. When trying to understand a model it sometimes helps to ask a policy question and see what the model offers. For example, one interesting question about marriage in the Social Security context is, What will

22. See Bumpass and Sweet (1989).

happen to the number of women eligible for spousal benefits? That question is policy relevant insofar as elderly women have historically been vulnerable to high poverty rates, but recent trends in female labor force participation are poised to ameliorate the condition of future cohorts.[23,24] The longitudinal marital patterns presented in this paper and implemented within the context of a larger micro simulation permit an illustration of how the distribution of marital outcomes varies across women with different lifetime income.

Table 10 addresses the above question. It presents the percentage of *nonwidowed* women ages 62 to 67 who are eligible to draw OAI spouse benefits. The relevance of controlling for widowhood warrants a brief explanation. As male mortality rates decline, the number of husbands increases, thus increasing overall spouse eligibility. This “mortality improvement” confounds the effect of the retreat from marriage described above. Once the marital status composition is controlled for, two trends stand out. The first, going down a given column, suggests that women with lower lifetime earnings are more likely to be eligible for spouse benefits than are their richer counterparts. In 2005, 95 percent of women in the lowest lifetime earnings decile will be covered by their spouse’s earnings while only 77 percent of women in the highest decile will be comparably covered. This paper does not address whether these women stay married because they are likely low earners or if they are low earners because they know they are likely to stay married.

The second trend, reading the rows across, suggests that the probability of a low-earning woman losing OAI spouse coverage is greater than the probability of a high-earning woman

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23. Social Security Administration (2000).

24. Labor force participation is also forecast; currently it is modeled as a nested logit where participation is a function of age, sex, marital status, birth cohort, and beneficiary status.

losing that coverage. The estimated change in coverage among the lowest decile of nonwidowed women is eight percentage points, from 95 percent in 2005 to 87 percent by 2075. The comparable decline for women in the highest decile is only five percentage points.

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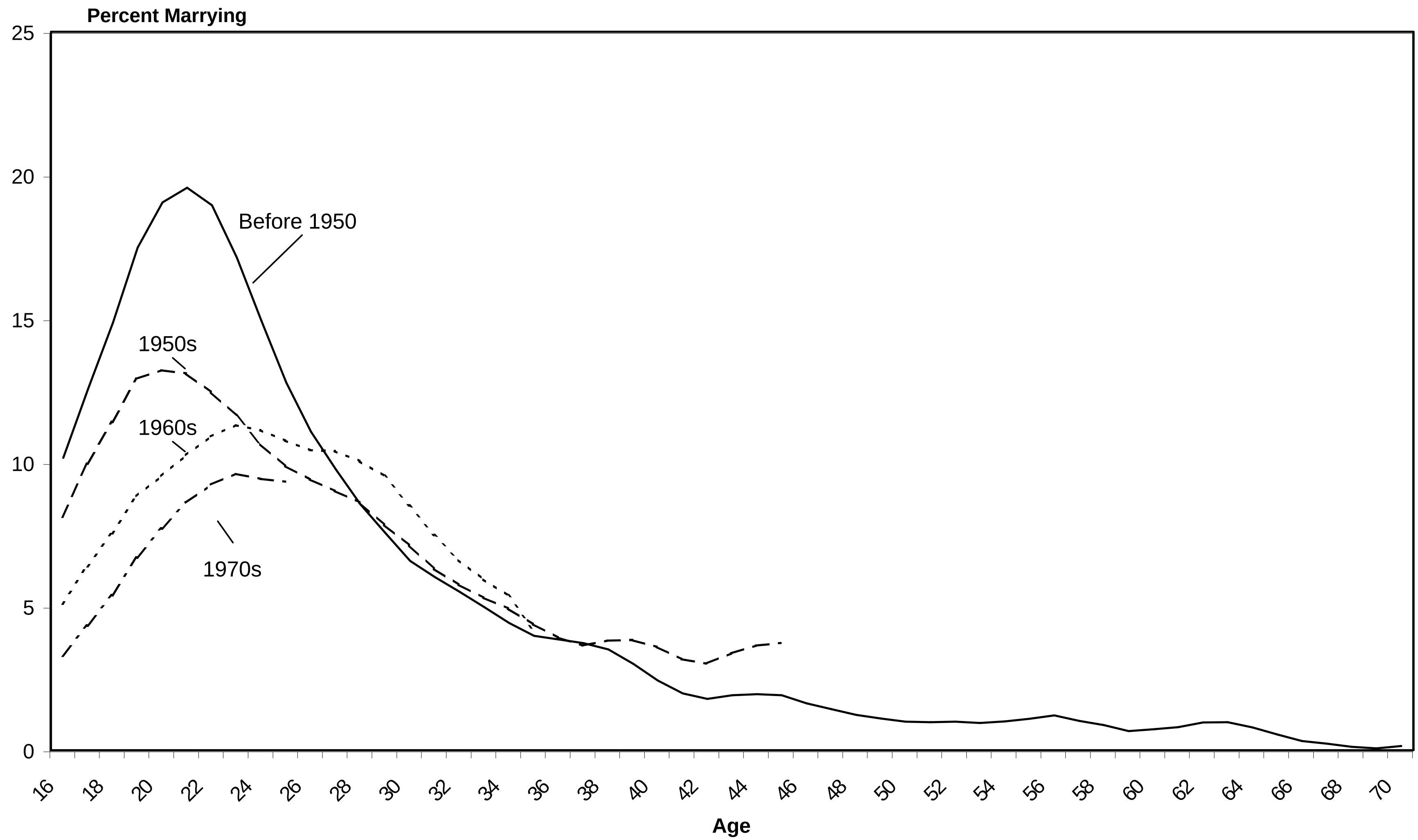
Table 1.
Comparison of Marital Transition Rates in SIPP and Vital Statistics (NCHS) Data

	Men	Women
First Marriage Rate (Per 1,000 People)		
SIPP (1995)	48.6	58.3
NCHS (1990)	47.0	57.7
Divorce Rate (Per 1,000 People)		
SIPP (1995)	14.5	17.4
NCHS (1990)	19.2	18.7
Remarriage Rate (Per 1,000 People)		
SIPP (1995)	73.2	38.9
NCHS (1990)	84.5	35.8

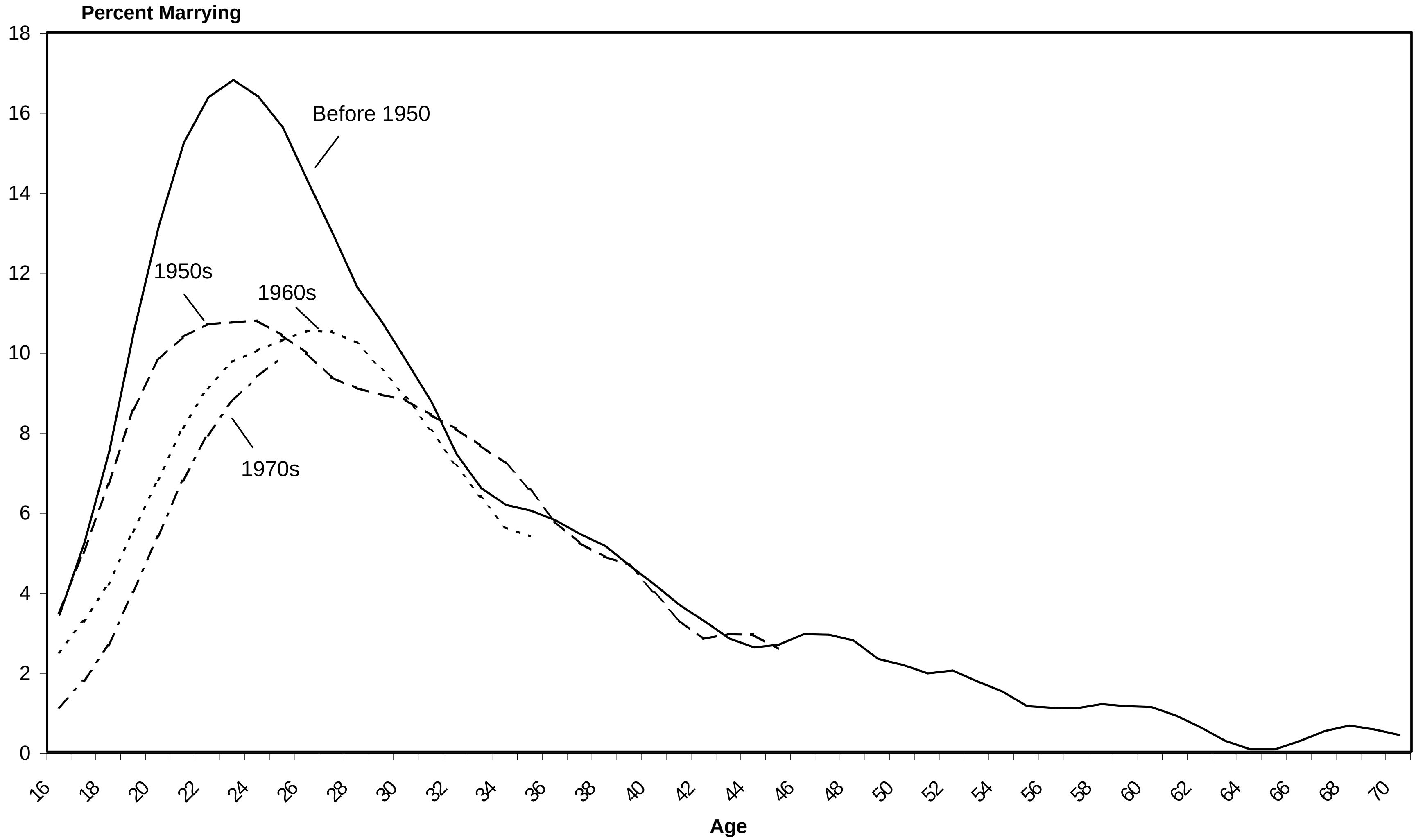
Note: SIPP = Survey of Income and Program Participation
NCHS = National Center for Health Statistics

Figure 1: Female First Marriage Rates by Cohort and Age



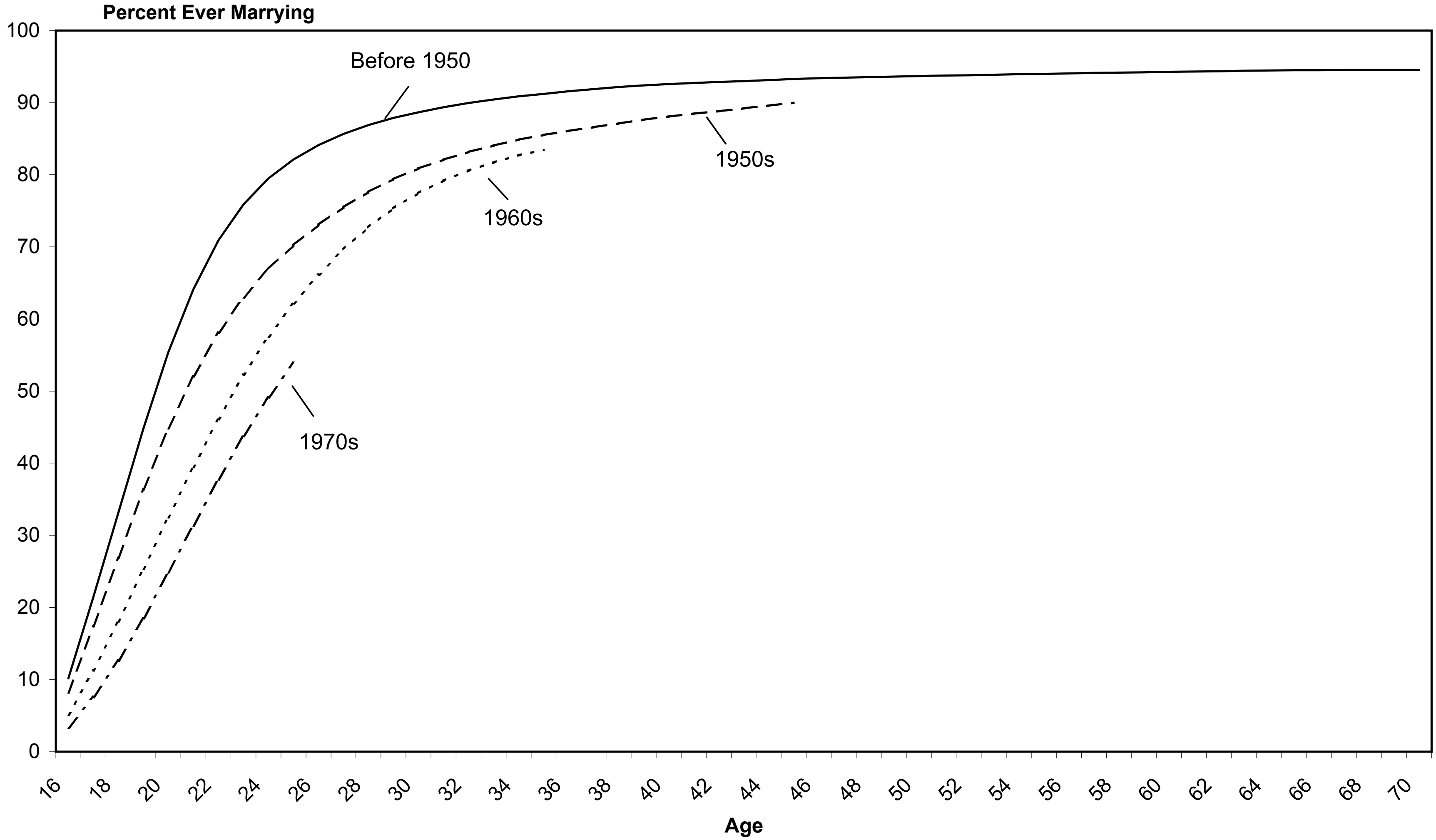
Source: Congressional Budget Office based on data from the 1996 Survey of Income and Program Participation.

Figure 2: Male First Marriage Rates by Cohort and Age



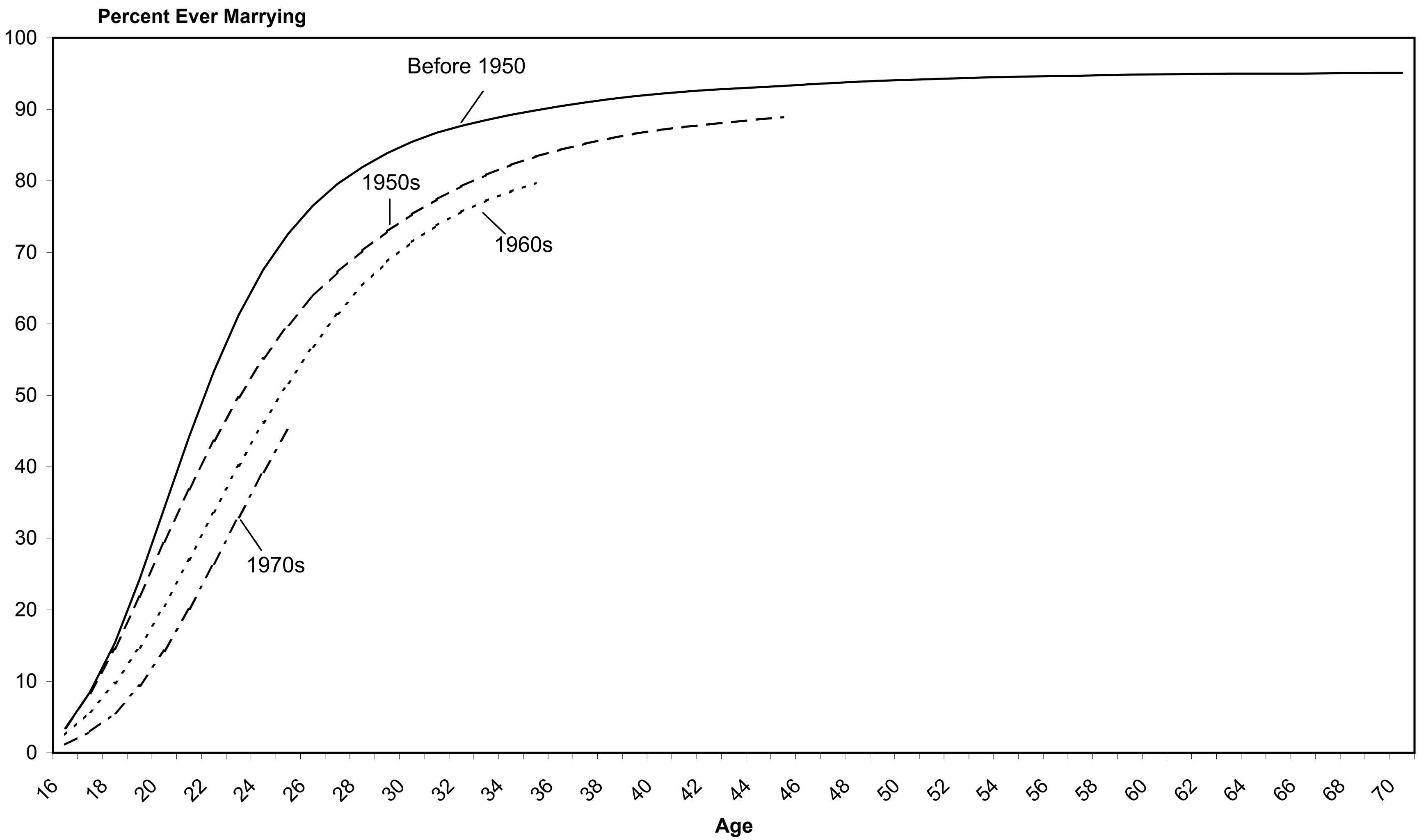
Source: Congressional Budget Office based on data from the 1996 Survey of Income and Program Participation.

Figure 3: Female Cumulative First Marriage Probabilities by Cohort and Age



Source: Congressional Budget Office based on data from the 1996 Survey of Income and Program Participation.

Figure 4: Male Cumulative First Marriage Probabilities by Cohort and Age



Source: Congressional Budget Office based on data from the 1996 Survey of Income and Program Participation.

Table 2.
Age-Centered Regression Coefficients, Female First Marriage

Age Group	**Coefficient on:** Age	Educ.	Income	Cohort50	Cohort60	Cohort70	Constant
17	**0.4078**	**-1.2836**	**0.0505**	**-0.1849**	**-0.7488**	**-1.3069**	**-8.8695**
18	**0.1984**	**-0.9851**	**0.0646**	**-0.2654**	**-0.7750**	**-1.2554**	**-5.3802**
19	**0.1180**	**-0.6605**	**0.0687**	**-0.3493**	**-0.7948**	**-1.1919**	**-4.0094**
20	**0.0659**	**-0.4325**	**0.0692**	**-0.4082**	**-0.7761**	**-1.1156**	**-3.1019**
21	**0.0132**	**-0.2548**	**0.0652**	**-0.4492**	**-0.7397**	**-1.0336**	**-2.0682**
22	**-0.0232**	**-0.0900**	**0.0618**	**-0.4828**	**-0.6770**	**-0.9533**	**-1.3510**
23	**-0.0532**	**0.0513**	**0.0564**	**-0.4876**	**-0.5919**	**-0.8607**	**-0.7396**
24	**-0.0727**	**0.1578**	**0.0496**	**-0.4645**	**-0.4916**	**-0.7593**	**-0.3318**
25	**-0.0838**	**0.2281**	**0.0432**	**-0.4024**	**-0.3601**	**-0.6494**	-0.1167
26	**-0.0840**	**0.2624**	**0.0390**	**-0.3151**	**-0.2245**		-0.1754
27	**-0.0793**	**0.2945**	**0.0362**	**-0.2254**	**-0.1026**		**-0.3651**
28	**-0.0835**	**0.3008**	**0.0346**	**-0.1457**	-0.0056		-0.3108
29	**-0.0940**	**0.3058**	**0.0337**	**-0.0877**	0.0742		-0.0644
30	**-0.1042**	**0.2852**	**0.0340**	-0.0342	**0.1274**		0.2044
31	**-0.1142**	**0.2674**	**0.0309**	-0.0095	**0.1480**		0.5204
32	**-0.1114**	**0.2229**	**0.0295**	0.0093	**0.1486**		0.4556
33	**-0.1080**	**0.1985**	**0.0257**	0.0166	0.1408		0.3846
34	**-0.1009**	**0.1816**	**0.0224**	0.0332	0.1040		0.1813
35	**-0.0910**	**0.1917**	**0.0157**	0.0290	0.0497		-0.1097
36	**-0.0733**	0.1938	**0.0135**	0.0284			-0.7145
37	**-0.0724**	0.2457	**0.0068**	0.0432			-0.7342
38	**-0.0822**	0.2901	**0.0034**	0.0897			-0.3866
39	**-0.0928**	0.2675	**0.0022**	0.1479			0.0042
40	**-0.1096**	0.2058	0.0061	**0.2174**			0.6326
41	**-0.0974**	0.1301	0.0085	**0.3348**			0.1209
42	**-0.0704**	-0.0180	0.0147	**0.4543**			-1.0136
43	-0.0275	-0.2326	0.0202	**0.5487**			**-2.8201**
44	-0.0171	**-0.4013**	0.0197	**0.6266**			**-3.2628**
45	-0.0426	**-0.5414**	0.0165	**0.6478**			-2.0977
46	**-0.1045**	**-0.7567**	-0.0020				0.8374
47	**-0.1456**	**-0.7762**	-0.0145				2.8212
48	**-0.1245**	**-0.6992**	-0.0240				1.8959
49	**-0.1060**	-0.4757	-0.0248				0.9858
50	-0.0741	-0.4092	-0.0412				-0.5410
51	-0.0463	-0.3358	-0.0530				-1.8714
52	0.0067	-0.2539	-0.0525				-4.5669
53	0.0246	-0.2141	-0.0578				-5.5385
54	0.0383	-0.2991	**-0.0756**				-6.1978
55	-0.0063	-0.2090	**-0.0763**				-3.7633
56	-0.0514	-0.0590	**-0.0762**				-1.2904
57	-0.0860	-0.1108	**-0.0827**				0.6373
58	-0.1177	-0.2401	**-0.0986**				2.5872
59	-0.1025	-0.3964	**-0.0975**				1.7546
60	-0.0212	-0.6622	**-0.0912**				-3.0412

Note: Coefficients in **BOLD** are significant at the 90 percent level.

Table 3.
Age-Centered Regression Coefficients, Male First Marriage

Age Group	Age	Educ.	Income	Cohort50	Cohort60	Cohort70	Constant
	Coefficient on:						
17	**0.5626**	**-1.0578**	**0.0778**	0.0000	**-0.4407**	**-1.2186**	**-12.8694**
18	**0.3540**	**-0.8410**	**0.0891**	**-0.1243**	**-0.6510**	**-1.1558**	**-9.2769**
19	**0.2512**	**-0.5673**	**0.0890**	**-0.2672**	**-0.7204**	**-1.0829**	**-7.4000**
20	**0.1761**	**-0.3767**	**0.0859**	**-0.3591**	**-0.7265**	**-1.0163**	**-5.9724**
21	**0.1187**	**-0.2460**	**0.0793**	**-0.4191**	**-0.7196**	**-0.9445**	**-4.7703**
22	**0.0705**	**-0.1339**	**0.0740**	**-0.4628**	**-0.6910**	**-0.8824**	**-3.7333**
23	**0.0277**	**-0.0372**	0.0680	**-0.4944**	**-0.6512**	**-0.8263**	**-2.7730**
24	-0.0062	**0.0453**	**0.0626**	**-0.4967**	**-0.5944**	**-0.7504**	**-1.9937**
25	**-0.0316**	**0.1084**	**0.0585**	**-0.4842**	**-0.5204**	**-0.6805**	**-1.3986**
26	**-0.0497**	**0.1596**	**0.0550**	**-0.4417**	**-0.4370**		**-0.9735**
27	**-0.0590**	**0.2023**	**0.0534**	**-0.3964**	**-0.3607**		**-0.7759**
28	**-0.0639**	**0.2371**	**0.0537**	**-0.3281**	**-0.2780**		**-0.7048**
29	**-0.0717**	**0.2678**	**0.0535**	**-0.2575**	**-0.2134**		**-0.5385**
30	**-0.0765**	**0.2896**	**0.0522**	**-0.1731**	**-0.1607**		**-0.4452**
31	**-0.0782**	**0.3218**	**0.0486**	**-0.1033**	**-0.1307**		-0.4086
32	**-0.0866**	**0.3404**	**0.0429**	-0.0179	**-0.1105**		-0.1495
33	**-0.0899**	**0.3644**	**0.0379**	0.0345	-0.1166		-0.0369
34	**-0.0802**	**0.3993**	**0.0366**	0.0468	-0.1225		-0.3564
35	**-0.0741**	**0.4259**	**0.0359**	0.0410	-0.1457		-0.5621
36	**-0.0725**	**0.4104**	**0.0361**	0.0257			-0.6189
37	**-0.0762**	**0.4474**	**0.0416**	-0.0314			-0.5162
38	**-0.0905**	**0.4715**	**0.0453**	-0.0809			0.0098
39	**-0.0990**	**0.4521**	**0.0444**	-0.0867			0.3427
40	**-0.1062**	**0.4707**	**0.0418**	-0.1204			0.6351
41	**-0.1299**	**0.4741**	**0.0416**	-0.1419			1.6004
42	**-0.1231**	**0.3462**	**0.0424**	-0.1272			1.3771
43	**-0.0757**	0.1881	**0.0495**	-0.0826			-0.6233
44	-0.0359	0.1113	**0.0599**	-0.0970			-2.4015
45	-0.0104	-0.0477	**0.0806**	-0.0547			**-3.6654**
46	0.0142	-0.1178	**0.0967**				**-4.8912**
47	-0.0149	-0.1106	**0.1082**				**-3.6658**
48	-0.0432	-0.0940	**0.1066**				-2.3195
49	**-0.0738**	-0.1186	**0.0996**				-0.7745
50	**-0.0903**	-0.0423	**0.0837**				0.1637
51	**-0.0863**	-0.0259	**0.0619**				0.0935
52	**-0.0860**	0.0766	0.0359				0.2574
53	**-0.1133**	0.1095	0.0175				1.7711
54	**-0.1305**	0.2696	0.0056				2.7245
55	-0.1141	0.2572	-0.0050				1.9071
56	-0.1018	0.2967	0.0001				1.2352
57	-0.0114	0.3009	0.0059				-3.9150
58	0.0047	0.4180	0.0114				-4.9085
59	-0.0534	0.3186	0.0047				-1.5017
60	-0.1370	0.4306	0.0080				3.3958

Note: Coefficients in **BOLD** are significant at the 90 percent level.

Table 4.
Age-Centered Regression Coefficients, Female Divorce

Age	**Coefficient on:**								
Group	**Age**	**Educ**	**Duration**	**Durat Sq**	**Income**	**Prev Marr**	**Cohort50**	**Cohort60**	**Constant**
17	0.0543	0.2758	0.0000	0.0161	0.0604		0.4342	**0.9722**	-5.1091
18	-0.0097	0.1493	-0.1871	0.1004	**0.0704**		**0.6378**	**0.9239**	**-3.9443**
19	**-0.1305**	**0.1641**	**0.2359**	0.0066	**0.0897**		**0.7421**	**1.0766**	**-2.2157**
20	**-0.1777**	**0.1270**	**0.3546**	**-0.0145**	**0.0897**		**0.7757**	**1.1460**	**-1.4277**
21	**-0.1821**	0.1042	**0.3838**	**-0.0198**	**0.0899**		**0.7881**	**1.1581**	**-1.3668**
22	**-0.1757**	0.0708	**0.3707**	**-0.0198**	**0.0874**		**0.7996**	**1.1335**	**-1.4377**
23	**-0.1648**	0.0306	**0.3462**	**-0.0186**	**0.0848**		**0.7830**	**1.0674**	**-1.5608**
24	**-0.1498**	0.0016	**0.3161**	**-0.0172**	**0.0837**		**0.7604**	**0.9687**	**-1.7622**
25	**-0.1491**	0.0201	**0.3012**	**-0.0154**	**0.0859**	**0.6304**	**0.7155**	**0.8218**	**-1.7486**
26	**-0.1334**	0.0049	**0.2592**	**-0.0127**	**0.0863**	**0.6340**	**0.6721**	**0.6813**	**-1.9579**
27	**-0.1215**	-0.0114	**0.2108**	**-0.0096**	**0.0868**	**0.6064**	**0.6191**	**0.5448**	**-2.0599**
28	**-0.1048**	-0.0300	**0.1719**	**-0.0075**	**0.0882**	**0.6035**	**0.5699**	**0.4142**	**-2.3213**
29	**-0.0861**	-0.0505	**0.1336**	**-0.0055**	**0.0874**	**0.6136**	**0.5154**	**0.3073**	**-2.6473**
30	**-0.0694**	**-0.0846**	**0.1041**	**-0.0041**	**0.0871**	**0.6158**	**0.4697**	**0.2288**	**-2.9740**
31	**-0.0523**	**-0.1223**	**0.0840**	**-0.0032**	**0.0861**	**0.6164**	**0.4390**	**0.1573**	**-3.3570**
32	**-0.0443**	**-0.1410**	**0.0744**	**-0.0030**	**0.0865**	**0.6207**	**0.3988**	0.0999	**-3.5204**
33	**-0.0398**	**-0.1331**	**0.0554**	**-0.0021**	**0.0857**	**0.6185**	**0.3712**	0.0637	**-3.5659**
34	**-0.0390**	**-0.1116**	**0.0522**	**-0.0020**	**0.0863**	**0.6229**	**0.3536**	0.0199	**-3.5703**
35	**-0.0485**	-0.0593	**0.0420**	**-0.0016**	**0.0840**	**0.6180**	**0.3309**	-0.0434	**-3.1774**
36	**-0.0574**	0.0327	**0.0408**	**-0.0016**	**0.0830**	**0.5967**	**0.2954**		**-2.8440**
37	**-0.0650**	0.0796	**0.0338**	**-0.0014**	**0.0767**	**0.6298**	**0.2938**		**-2.5039**
38	**-0.0726**	**0.1074**	0.0254	-0.0011	**0.0725**	**0.6581**	**0.2656**		**-2.1389**
39	**-0.0761**	**0.1306**	0.0132	-0.0007	**0.0674**	**0.6709**	**0.2280**		**-1.8909**
40	**-0.0713**	**0.1437**	0.0075	-0.0006	**0.0637**	**0.6954**	**0.2096**		**-2.0240**
41	**-0.0629**	**0.1395**	-0.0004	-0.0003	**0.0621**	**0.6993**	**0.1824**		**-2.2789**
42	**-0.0495**	**0.1493**	-0.0070	0.0000	**0.0638**	**0.7239**	**0.1190**		**-2.8274**
43	**-0.0432**	**0.1678**	-0.0042	-0.0001	**0.0627**	**0.7327**	0.1014		**-3.1162**
44	**-0.0409**	**0.2085**	-0.0008	-0.0003	**0.0621**	**0.7434**	0.0841		**-3.2389**
45	**-0.0482**	**0.2429**	0.0002	-0.0004	**0.0637**	**0.7490**	-0.0144		**-2.9070**
46	**-0.0444**	**0.2635**	0.0116	-0.0008	**0.0657**	**0.7489**			**-3.1332**
47	**-0.0434**	**0.2572**	0.0120	-0.0009	**0.0605**	**0.7521**			**-3.0950**
48	**-0.0532**	**0.2318**	0.0109	-0.0010	**0.0593**	**0.7411**			**-2.5465**
49	**-0.0532**	0.1314	0.0173	**-0.0013**	**0.0618**	**0.7368**			**-2.5271**
50	**-0.0380**	0.0346	0.0281	**-0.0017**	**0.0614**	**0.7013**			**-3.2604**
51	-0.0361	-0.0345	0.0346	**-0.0020**	**0.0619**	**0.6379**			**-3.3134**
52	-0.0378	-0.0838	**0.0491**	**-0.0024**	**0.0676**	**0.5849**			**-3.2983**
53	**-0.0458**	-0.1341	**0.0651**	**-0.0028**	**0.0701**	**0.5816**			**-3.0124**
54	**-0.0452**	-0.0628	**0.0671**	**-0.0028**	**0.0663**	**0.5461**			**-3.0347**
55	**-0.0561**	0.0207	**0.0552**	**-0.0025**	**0.0600**	**0.5374**			-2.3724
56	**-0.0573**	0.1384	0.0383	**-0.0020**	**0.0581**	**0.5230**			-2.1941
57	**-0.0578**	0.2248	0.0137	**-0.0014**	**0.0482**	**0.4981**			-1.9207
58	-0.0377	0.3774	-0.0189	-0.0008	**0.0353**	**0.4333**			-2.6780
59	-0.0024	**0.4647**	-0.0297	-0.0006	**0.0341**	**0.4387**			**-4.6634**
60	0.0097	**0.4895**	-0.0185	-0.0009	**0.0422**	**0.4158**			**-5.4251**
61	0.0035	**0.5604**	0.0014	**-0.0014**	**0.0405**	**0.4452**			**-5.2106**
62	-0.0120	**0.6306**	0.0363	**-0.0023**	**0.0461**	0.4314			-4.5039
63	-0.0098	**0.7281**	**0.0748**	**-0.0031**	**0.0631**	0.4435			-5.0705
64	-0.0727	**0.7160**	**0.0832**	**-0.0033**	**0.0611**	0.3757			-1.0626
65	-0.0958	**0.6852**	**0.0845**	**-0.0033**	0.0575	0.4366			0.3086
66	-0.0994	0.5004	0.0579	**-0.0026**	**0.0657**	0.4600			0.7356
67	-0.0379	0.2292	0.0042	-0.0012	**0.0912**	**0.6709**			-3.2858
68	0.0464	-0.1925	-0.0345	-0.0002	**0.1144**	0.8795			-9.0234
69	0.0862	0.1137	-0.0368	0.0000	**0.1551**	1.0658			-12.2533
70	0.0605	0.3973	-0.0539	0.0004	**0.2015**	1.0900			-10.5904

Note: Coefficients in **BOLD** are significant at the 90 percent level.

Table 5.
Age-Centered Regression Coefficients, Male Divorce

Age	**Coefficient on:**								
Group	**Age**	**Educ.**	**Duration**	**Durat Sq**	**Income**	**Prev Marr**	**Cohort50**	**Cohort60**	**Constant**
17	**-1.1723**	-1.6886	0.1394	0.1394	0.1472		0.8718	1.1750	15.5299
18	-0.1229	0.1031	**-1.0627**	**0.3932**	**0.0781**		**0.6675**	**1.1775**	-1.6450
19	**-0.1372**	**0.2257**	-0.0149	**0.0898**	**0.0383**		**0.6617**	**1.1010**	**-1.6426**
20	**-0.2106**	**0.1728**	**0.2063**	**0.0271**	**0.0201**		**0.7039**	**1.0119**	-0.0718
21	**-0.2233**	0.1190	**0.2824**	0.0090	0.0154		**0.7164**	**0.9764**	0.2337
22	**-0.2221**	0.0498	**0.3217**	-0.0028	0.0111		**0.7339**	**0.9544**	0.2774
23	**-0.2164**	-0.0224	**0.3470**	**-0.0103**	0.0065		**0.7311**	**0.8917**	0.2459
24	**-0.2004**	**-0.1067**	**0.3411**	**-0.0131**	0.0022		**0.7155**	**0.8311**	0.0256
25	**-0.1886**	**-0.1449**	**0.3399**	**-0.0146**	-0.0017	**0.5890**	**0.6988**	**0.7637**	-0.1720
26	**-0.1657**	**-0.1796**	**0.3101**	**-0.0136**	-0.0082	**0.6695**	**0.6650**	**0.6845**	**-0.5560**
27	**-0.1473**	**-0.1910**	**0.2883**	**-0.0128**	**-0.0142**	**0.7271**	**0.6302**	**0.5915**	**-0.8715**
28	**-0.1324**	**-0.1951**	**0.2612**	**-0.0113**	**-0.0181**	**0.7615**	**0.6056**	**0.5070**	**-1.1242**
29	**-0.1174**	**-0.1814**	**0.2322**	**-0.0098**	**-0.0210**	**0.7695**	**0.5883**	**0.4096**	**-1.3952**
30	**-0.1074**	**-0.1824**	**0.2012**	**-0.0082**	**-0.0231**	**0.7497**	**0.5443**	**0.2995**	**-1.5148**
31	**-0.0967**	**-0.1944**	**0.1688**	**-0.0067**	**-0.0222**	**0.6919**	**0.5297**	**0.2096**	**-1.6719**
32	**-0.0838**	**-0.2185**	**0.1399**	**-0.0055**	**-0.0201**	**0.6283**	**0.5052**	0.1259	**-1.9149**
33	**-0.0705**	**-0.2334**	**0.1071**	**-0.0041**	**-0.0191**	**0.5853**	**0.4727**	0.0527	**-2.1666**
34	**-0.0611**	**-0.2592**	**0.0861**	**-0.0034**	**-0.0172**	**0.5722**	**0.4298**	-0.0044	**-2.3554**
35	**-0.0523**	**-0.2633**	**0.0700**	**-0.0028**	**-0.0150**	**0.5757**	**0.4151**	-0.0512	**-2.5707**
36	**-0.0492**	**-0.2357**	**0.0658**	**-0.0027**	**-0.0145**	**0.5836**	**0.3743**		**-2.6462**
37	**-0.0453**	**-0.2078**	**0.0551**	**-0.0023**	**-0.0169**	**0.6282**	**0.3196**		**-2.7123**
38	**-0.0426**	**-0.1799**	**0.0476**	**-0.0020**	**-0.0189**	**0.6404**	**0.2534**		**-2.7369**
39	**-0.0454**	**-0.1269**	**0.0386**	**-0.0017**	**-0.0227**	**0.6350**	**0.1962**		**-2.5360**
40	**-0.0442**	-0.0915	**0.0383**	**-0.0017**	**-0.0262**	**0.6566**	0.0997		**-2.5428**
41	**-0.0414**	-0.0352	0.0314	**-0.0015**	**-0.0296**	**0.6637**	0.0051		**-2.5746**
42	**-0.0394**	0.0052	0.0244	-0.0013	**-0.0314**	**0.6574**	-0.0674		**-2.5969**
43	**-0.0326**	0.0604	0.0175	-0.0011	**-0.0326**	**0.6647**	-0.1432		**-2.8334**
44	-0.0204	0.0874	0.0202	**-0.0013**	**-0.0314**	**0.6681**	**-0.2542**		**-3.3595**
45	-0.0264	**0.1461**	0.0139	-0.0012	**-0.0307**	**0.6392**	**-0.3389**		**-3.0313**
46	**-0.0346**	**0.1865**	0.0074	-0.0010	**-0.0275**	**0.5919**			**-2.6187**
47	**-0.0566**	**0.1652**	0.0037	-0.0011	**-0.0265**	**0.5580**			**-1.5193**
48	**-0.0852**	0.0948	0.0039	**-0.0012**	**-0.0285**	**0.5429**			-0.0944
49	**-0.1000**	0.0356	-0.0045	-0.0010	**-0.0324**	**0.5155**			0.7462
50	**-0.0899**	-0.0500	-0.0066	-0.0010	**-0.0383**	**0.4857**			0.3825
51	**-0.0648**	-0.1122	-0.0007	**-0.0012**	**-0.0467**	**0.4545**			-0.7630
52	-0.0390	-0.1313	0.0036	-0.0014	**-0.0527**	**0.4397**			-2.0632
53	-0.0032	-0.0422	0.0063	-0.0015	**-0.0524**	**0.3654**			**-3.8923**
54	0.0109	0.0588	0.0148	**-0.0018**	**-0.0516**	**0.3155**			**-4.6891**
55	0.0163	0.0940	0.0277	**-0.0021**	**-0.0499**	**0.2724**			**-5.0848**
56	0.0067	0.1473	0.0347	**-0.0022**	**-0.0448**	**0.2560**			**-4.6894**
57	-0.0215	0.1545	0.0482	**-0.0025**	**-0.0413**	**0.2417**			**-3.2256**
58	**-0.0655**	0.0909	**0.0625**	**-0.0027**	**-0.0395**	**0.2495**			-0.9003
59	**-0.0745**	-0.0350	**0.0861**	**-0.0033**	**-0.0368**	0.2233			-0.5297
60	**-0.0760**	-0.0742	**0.0876**	**-0.0032**	-0.0302	0.2632			-0.5605
61	-0.0587	-0.1367	**0.0876**	**-0.0031**	-0.0269	0.2939			-1.6836
62	-0.0252	-0.0746	**0.0789**	**-0.0028**	-0.0233	0.3129			-3.8189
63	-0.0451	-0.0093	0.0630	**-0.0024**	**-0.0257**	0.3749			-2.5349
64	-0.0660	0.1021	0.0286	-0.0014	-0.0245	**0.5238**			-1.2080
65	-0.1109	0.1424	0.0196	-0.0012	-0.0334	**0.5892**			1.6943
66	**-0.1260**	0.2046	0.0298	-0.0014	-0.0319	**0.6737**			2.4686
67	**-0.1419**	0.1018	0.0324	-0.0014	-0.0249	**0.8168**			3.3959
68	-0.0786	0.1695	0.0278	-0.0013	-0.0053	**0.9273**			-0.9322
69	-0.0690	0.1962	0.0364	-0.0015	0.0262	**1.0116**			-1.8784
70	-0.0489	0.2294	0.0282	-0.0013	0.0802	**1.0093**			-3.4575

Note: Coefficients in **BOLD** are significant at the 90 percent level.

Table 6.
Age-Centered Regression Coefficients, Female Remarriage

Age Group	**Coefficient on:**								
	Age	**Educ.**	**Duration**	**Durat Sq**	**Income**	**Prev Marr**	**Cohort50**	**Cohort60**	**Constant**
17	0.0143	0.7561	**0.5913**	-0.9115	0.0663		**-0.9232**	**-0.8718**	-0.5290
18	**-0.1778**	-0.2285	**0.2924**	**-0.2813**	0.0252		**-0.7318**	**-0.9164**	**3.0791**
19	**-0.1949**	**-0.4663**	**0.2486**	**-0.1067**	0.0255		**-0.5442**	**-0.5765**	**3.1503**
20	**-0.1363**	**-0.4542**	**0.3237**	**-0.0924**	**0.0237**		**-0.4023**	**-0.3827**	**1.7917**
21	**-0.1245**	**-0.4015**	**0.3420**	**-0.0834**	**0.0253**		**-0.3065**	**-0.2613**	**1.4120**
22	**-0.1189**	**-0.3028**	**0.3244**	**-0.0666**	**0.0278**		**-0.2261**	**-0.1769**	**1.1702**
23	**-0.1086**	**-0.1968**	**0.2946**	**-0.0542**	**0.0301**		**-0.1678**	-0.1223	**0.8531**
24	**-0.0937**	-0.1032	**0.2800**	**-0.0478**	**0.0323**		-0.1101	-0.0683	0.4174
25	**-0.0800**	-0.0329	**0.2556**	**-0.0401**	**0.0321**	0.0101	-0.0941	-0.0245	0.0307
26	**-0.0646**	0.0161	**0.2298**	**-0.0341**	**0.0299**	0.0060	-0.0978	-0.0245	-0.3522
27	**-0.0535**	0.0381	**0.2096**	**-0.0296**	**0.0269**	-0.0099	-0.0981	-0.0208	**-0.6136**
28	**-0.0515**	0.0288	**0.1959**	**-0.0272**	**0.0241**	-0.0191	-0.0954	-0.0185	**-0.6352**
29	**-0.0560**	0.0135	**0.1728**	**-0.0234**	**0.0214**	-0.0168	-0.0858	-0.0352	-0.4736
30	**-0.0670**	-0.0018	**0.1441**	**-0.0195**	**0.0201**	-0.0360	-0.0615	-0.0811	-0.0918
31	**-0.0741**	-0.0255	**0.1160**	**-0.0160**	**0.0200**	-0.0527	-0.0232	-0.0924	0.1658
32	**-0.0823**	-0.0506	**0.0883**	**-0.0130**	**0.0214**	-0.0353	-0.0119	**-0.1402**	0.4306
33	**-0.0866**	-0.0522	**0.0665**	**-0.0105**	**0.0226**	-0.0413	-0.0109	**-0.2112**	0.6017
34	**-0.0822**	-0.0589	**0.0438**	**-0.0081**	**0.0234**	-0.0487	-0.0391	**-0.2625**	0.5014
35	**-0.0787**	-0.0783	0.0292	**-0.0066**	**0.0243**	-0.0573	-0.0794	**-0.2736**	0.4214
36	**-0.0697**	-0.0837	0.0205	**-0.0056**	**0.0238**	-0.0795	**-0.1346**		0.1608
37	**-0.0634**	-0.0538	0.0109	**-0.0046**	**0.0216**	**-0.1237**	**-0.1599**		0.0157
38	**-0.0583**	-0.0610	0.0016	**-0.0038**	**0.0205**	**-0.1380**	**-0.1726**		-0.1354
39	**-0.0647**	-0.0691	-0.0001	**-0.0035**	**0.0211**	**-0.1492**	**-0.1754**		0.1119
40	**-0.0680**	-0.0590	0.0004	**-0.0034**	**0.0192**	**-0.1545**	**-0.1700**		0.2549
41	**-0.0754**	-0.0925	0.0007	**-0.0032**	**0.0181**	**-0.1539**	**-0.1605**		0.5579
42	**-0.0683**	**-0.1399**	0.0026	**-0.0032**	**0.0204**	**-0.1511**	**-0.1762**		0.2533
43	**-0.0553**	**-0.1707**	-0.0022	**-0.0027**	**0.0211**	**-0.1659**	**-0.2206**		-0.2760
44	**-0.0531**	**-0.1818**	-0.0145	-0.0019	**0.0189**	**-0.1659**	**-0.2771**		-0.3157
45	**-0.0541**	**-0.2315**	-0.0229	-0.0014	**0.0217**	**-0.1512**	**-0.3605**		-0.2905
46	**-0.0690**	**-0.2418**	-0.0277	-0.0012	**0.0258**	**-0.1464**			0.3692
47	**-0.0825**	**-0.2581**	-0.0352	-0.0007	**0.0268**	-0.0960			0.9463
48	**-0.0947**	**-0.2619**	-0.0290	-0.0010	**0.0284**	-0.0517			1.4377
49	**-0.0806**	**-0.2762**	-0.0204	-0.0012	**0.0320**	-0.0486			0.7034
50	**-0.0718**	**-0.2290**	-0.0143	-0.0014	**0.0307**	-0.0552			0.2514
51	**-0.0750**	-0.1921	-0.0076	-0.0014	**0.0293**	-0.0660			0.3776
52	**-0.0891**	-0.0952	-0.0021	-0.0015	**0.0227**	-0.1118			1.1404
53	**-0.1046**	-0.0196	-0.0014	-0.0013	0.0206	-0.1434			1.9855
54	**-0.1061**	0.0350	0.0034	-0.0014	0.0217	-0.1448			2.0307
55	**-0.0927**	0.0531	0.0040	-0.0013	**0.0242**	-0.1196			1.2403
56	**-0.0781**	0.0505	0.0031	-0.0013	**0.0317**	-0.1030			0.3614
57	**-0.0816**	-0.0005	0.0007	-0.0013	**0.0449**	-0.0394			0.4282
58	**-0.0845**	-0.0311	-0.0047	-0.0012	**0.0508**	0.0143			0.5169
59	**-0.1220**	-0.0472	-0.0172	-0.0008	**0.0496**	0.1123			2.6162
60	**-0.1643**	-0.0373	-0.0233	-0.0007	**0.0484**	0.1548			**5.1012**
61	**-0.1800**	0.0209	-0.0296	-0.0004	**0.0411**	0.2158			**6.0408**
62	**-0.1545**	0.0586	-0.0474	0.0004	0.0308	0.2349			**4.5726**
63	**-0.1104**	0.0284	**-0.0576**	0.0009	0.0293	0.2098			1.8694
64	-0.0794	-0.0566	-0.0528	0.0009	0.0349	0.1243			-0.0556
65	-0.0724	-0.1079	-0.0489	0.0009	**0.0486**	0.0160			-0.4435
66	-0.0493	-0.2360	-0.0557	0.0013	**0.0645**	-0.1172			-1.8111
67	-0.0522	-0.2406	-0.0505	0.0011	**0.0816**	-0.1832			-1.6502
68	-0.0664	-0.2615	-0.0538	0.0011	**0.0880**	-0.1715			-0.6940
69	**-0.0957**	-0.2773	**-0.0707**	**0.0015**	**0.0857**	-0.2510			1.4962
70	**-0.1433**	-0.4711	**-0.0859**	**0.0019**	0.0645	-0.1665			4.8139

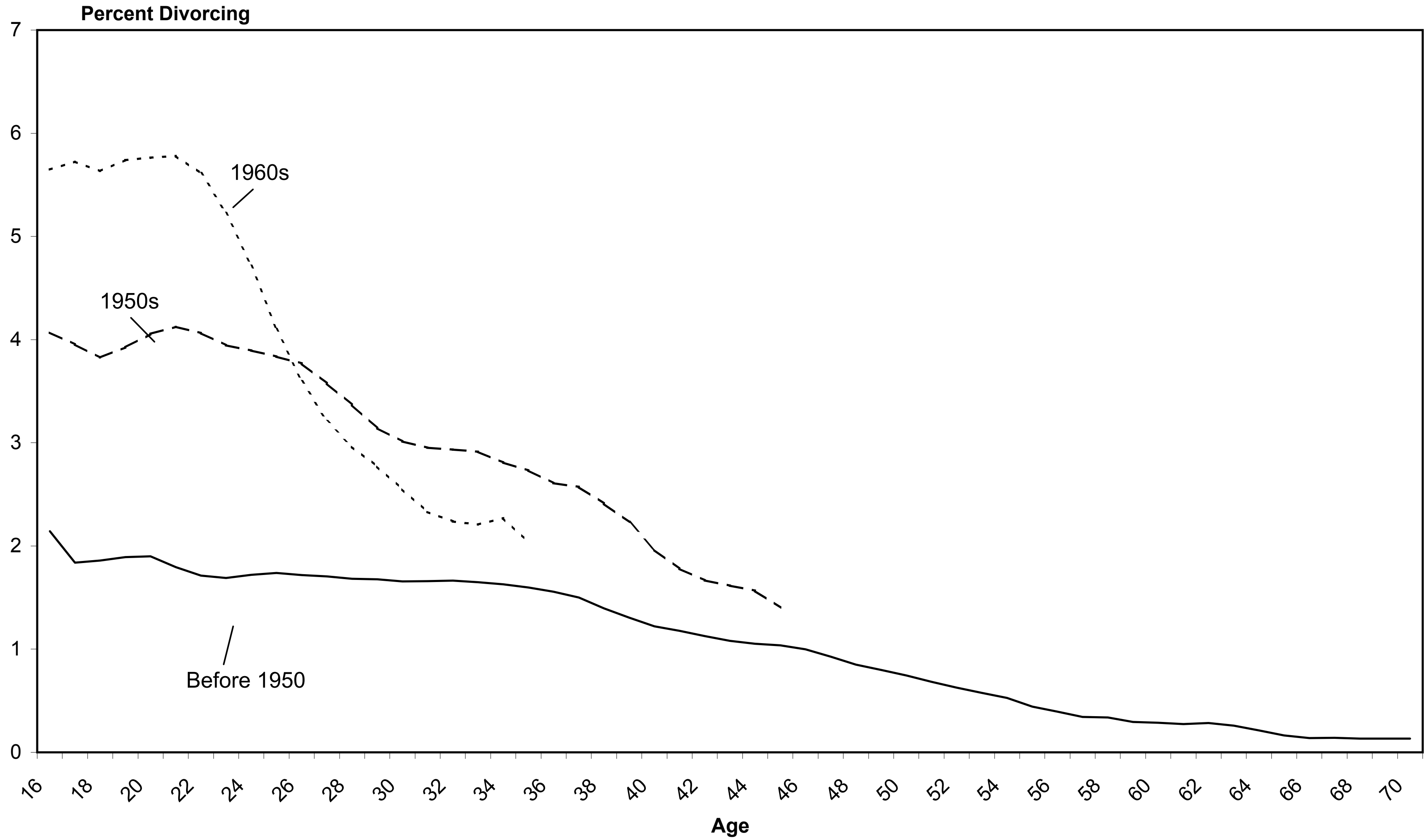
Note: Coefficients in **BOLD** are significant at the 90 percent level.

Table 7.
Age-Centered Regression Coefficients, Male Remarriage

Age	**Coefficient on:**								
Group	**Age**	**Educ.**	**Duration**	**Durat Sq**	**Income**	**Prev Marr**	**Cohort50**	**Cohort60**	**Constant**
17	-1.4174	-0.8372	**9.4046**	-8.7273	0.0154		-1.8340	-1.2695	24.1328
18	0.0623	0.4297	**0.9700**	**-0.4327**	0.0440		-0.2670	0.0398	-3.0280
19	-0.0380	0.0427	**0.8746**	**-0.3446**	**0.0440**		-0.2095	0.0268	**-1.0730**
20	-0.0096	0.0792	**0.7054**	**-0.2206**	**0.0479**		-0.1635	**-0.1636**	**-1.6572**
21	-0.0103	-0.0055	**0.6160**	**-0.1747**	**0.0420**		-0.1761	**-0.2398**	**-1.5588**
22	**-0.0179**	-0.0214	**0.5247**	**-0.1316**	**0.0410**		**-0.2928**	**-1.3694**	**-1.3694**
23	**-0.0343**	-0.0173	**0.4708**	**-0.1081**	**0.0418**		**-0.1809**	**-1.2951**	**-0.9823**
24	**-0.0413**	-0.0365	**0.3922**	**-0.0800**	**0.0375**		**-0.1716**	**-0.3066**	**-0.7804**
25	**-0.0473**	-0.0471	**0.3385**	**-0.0601**	**0.0359**	**0.5153**	**-0.1694**	**-0.2761**	**-1.1587**
26	**-0.0434**	-0.0270	**0.3026**	**-0.0489**	**0.0350**	**0.4289**	**-0.1629**	**-0.2484**	**-1.1786**
27	**-0.0335**	-0.0093	**0.2760**	**-0.0421**	**0.0336**	**0.3246**	**-0.1457**	**-0.2217**	**-1.3375**
28	**-0.0261**	-0.0115	**0.2608**	**-0.0380**	**0.0317**	0.2056	-0.1065	**-0.1855**	**-1.4333**
29	**-0.0276**	0.0019	**0.2404**	**-0.0340**	**0.0316**	0.1406	-0.0971	**-0.1831**	**-1.3233**
30	**-0.0314**	0.0155	**0.2136**	**-0.0297**	**0.0313**	0.0850	-0.0789	**-0.2016**	**-1.1374**
31	**-0.0388**	0.0177	**0.1886**	**-0.0261**	**0.0315**	0.0224	-0.0563	**-0.2196**	**-0.8351**
32	**-0.0411**	0.0190	**0.1695**	**-0.0234**	**0.0311**	-0.0282	-0.0516	**-0.2207**	**-0.6909**
33	**-0.0443**	0.0512	**0.1495**	**-0.0207**	**0.0316**	-0.0493	-0.0797	**-0.2659**	**-0.5392**
34	**-0.0452**	0.0774	**0.1303**	**-0.0186**	**0.0319**	-0.0953	-0.1006	**-0.2891**	**-0.4384**
35	**-0.0503**	0.1087	**0.1119**	**-0.0167**	**0.0317**	-0.1139	**-0.1378**	**-0.3318**	**-0.2148**
36	**-0.0566**	**0.1659**	**0.1040**	**-0.0154**	**0.0314**	-0.0853	**-0.1798**		-0.0158
37	**-0.0682**	**0.2144**	**0.0809**	**-0.0130**	**0.0337**	-0.0324	**-0.2395**		0.3622
38	**-0.0613**	**0.2402**	**0.0590**	**-0.0106**	**0.0369**	-0.0107	**-0.2735**		0.0840
39	**-0.0424**	**0.2603**	0.0447	**-0.0087**	**0.0380**	0.0156	**-0.2926**		-0.6705
40	-0.0257	**0.2886**	0.0330	**-0.0070**	**0.0394**	0.0333	**-0.3042**		**-1.3725**
41	-0.0168	**0.2974**	0.0172	**-0.0053**	**0.0397**	0.0224	**-0.3185**		**-1.7217**
42	**-0.0233**	**0.2778**	0.0080	**-0.0045**	**0.0378**	-0.0094	**-0.2831**		-1.3922
43	**-0.0375**	**0.2724**	0.0021	**-0.0040**	**0.0331**	-0.0267	**-0.2666**		-0.7198
44	**-0.0451**	**0.2701**	-0.0074	**-0.0034**	**0.0327**	-0.0252	-0.2594		-0.3722
45	**-0.0423**	**0.2235**	-0.0142	**-0.0034**	**0.0324**	-0.0424	-0.2172		-0.4302
46	**-0.0321**	**0.1831**	-0.0103	**-0.0039**	**0.0358**	-0.0595			-0.8846
47	-0.0239	**0.1664**	-0.0121	**-0.0038**	**0.0356**	-0.0804			-1.2291
48	-0.0154	0.1304	-0.0197	**-0.0033**	**0.0417**	-0.1106			**-1.6165**
49	-0.0250	0.0921	-0.0246	**-0.0031**	**0.0443**	**-0.1653**			-1.0912
50	-0.0371	0.1086	-0.0292	-0.0025	**0.0464**	**-0.2087**			-0.4639
51	-0.0317	0.1132	-0.0396	-0.0018	**0.0457**	**-0.2538**			-0.6494
52	-0.0258	0.1063	-0.0499	-0.0012	**0.0461**	**-0.3079**			-0.8603
53	-0.0134	0.1654	-0.0503	-0.0010	**0.0416**	**-0.3504**			-1.4577
54	-0.0076	**0.2310**	-0.0500	-0.0009	**0.0392**	**-0.3711**			-1.7423
55	-0.0056	**0.2626**	-0.0497	-0.0010	**0.0361**	**-0.3988**			-1.7909
56	-0.0042	**0.3318**	-0.0385	-0.0015	**0.0305**	**-0.3993**			-1.8824
57	-0.0145	**0.4630**	-0.0334	-0.0017	0.0226	**-0.3753**			-1.3327
58	-0.0513	**0.5173**	-0.0365	-0.0018	0.0148	**-0.3350**			0.7883
59	**-0.0818**	**0.5534**	-0.0432	-0.0016	0.0056	**-0.2960**			2.6038
60	**-0.0893**	**0.6313**	**-0.0481**	-0.0015	-0.0032	-0.2192			3.0104
61	**-0.0995**	**0.6743**	**-0.0649**	-0.0007	-0.0036	-0.1438			3.5539
62	**-0.0943**	**0.6556**	**-0.0800**	0.0001	-0.0009	-0.0613			3.1516
63	**-0.0988**	**0.6960**	**-0.0858**	0.0009	0.0004	-0.0093			3.3217
64	**-0.1326**	**0.7335**	**-0.0904**	0.0013	0.0005	0.0628			**5.3414**
65	**-0.1239**	**0.6982**	**-0.0995**	**0.0018**	0.0036	0.1046			**4.7363**
66	**-0.1160**	**0.7150**	**-0.1071**	**0.0021**	0.0022	0.1165			4.2463
67	-0.0760	**0.6866**	**-0.1205**	**0.0023**	-0.0034	0.1005			1.7064
68	-0.0223	**0.4795**	**-0.1446**	0.0026	-0.0105	0.1066			-1.7748
69	-0.0030	0.2762	**-0.1515**	**0.0024**	-0.0116	0.0291			-2.9089
70	-0.0152	0.1493	**-0.1464**	0.0018	-0.0084	-0.0882			-1.9173

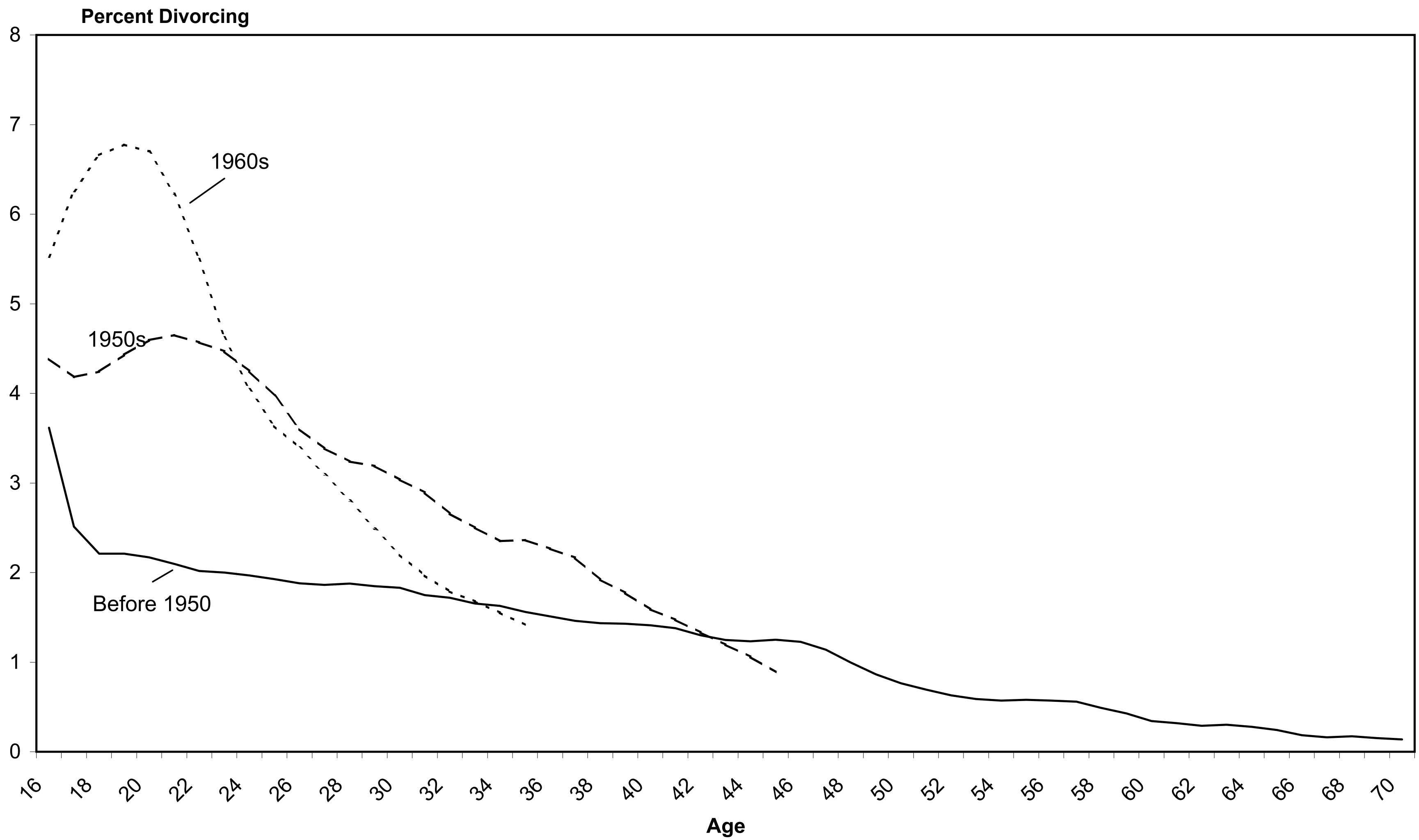
Note: Coefficients in **BOLD** are significant at the 90 percent level.

Figure 5: Female Divorce Rates by Cohort and Age



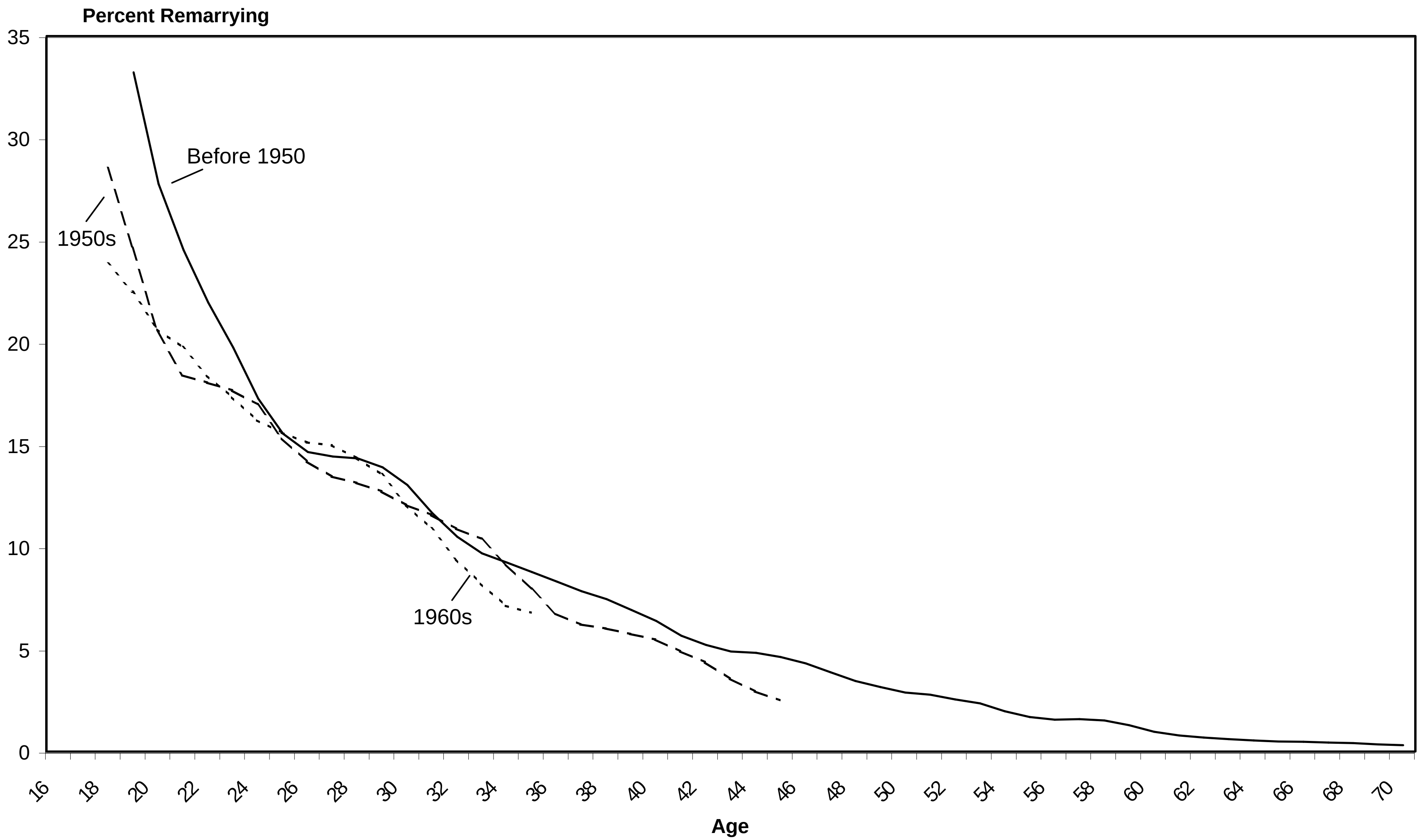
Source: Congressional Budget Office based on data from the 1996 Survey of Income and Program Participation.

Figure 6: Male Divorce Rates by Cohort and Age



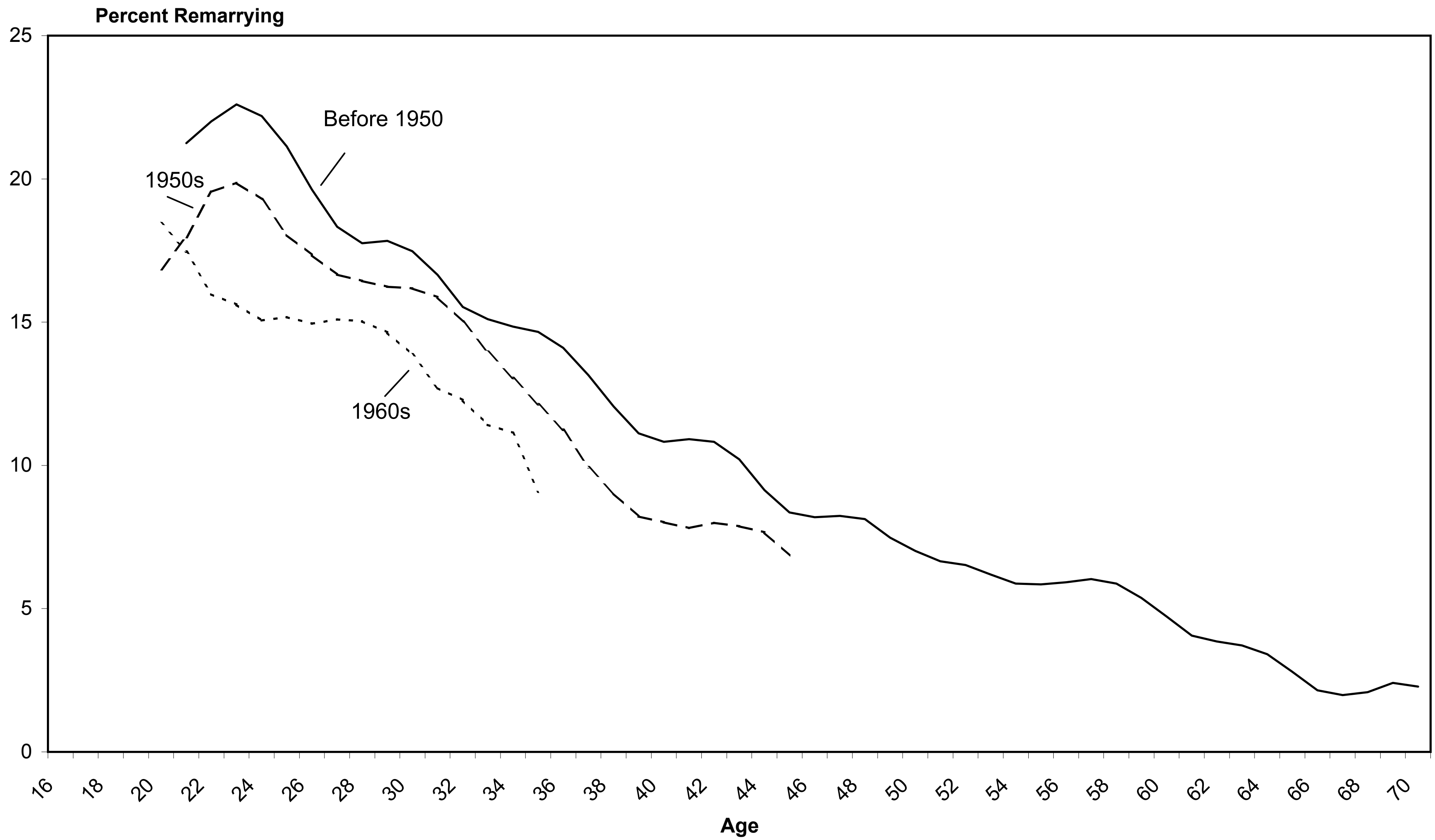
Source: Congressional Budget Office based on the data from the 1996 Survey of Income and Program Participation.

Figure 7: Female Remarriage Rates by Cohort and Age



Source: Congressional Budget Office based on data from the 1996 Survey of Income and Program Participation.

Figure 8: Male Remarriage Rates by Cohort and Age



Source: Congressional Budget Office based on data from the 1996 Survey of Income and Program Participation.

Figure 9: Residual Cohort Effects, Female First Marriage

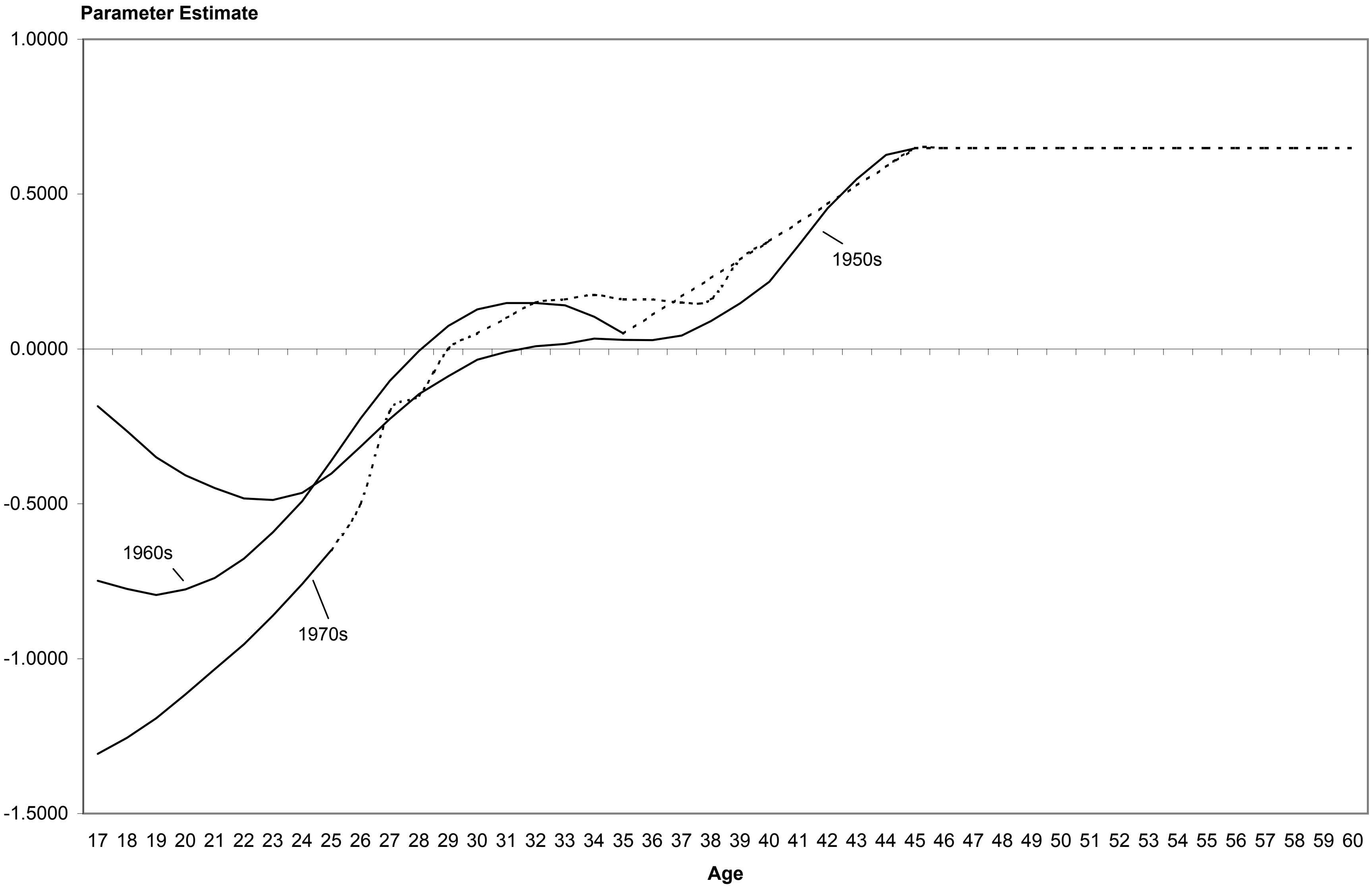


Figure 10: Residual Cohort Effects, Male First Marriage

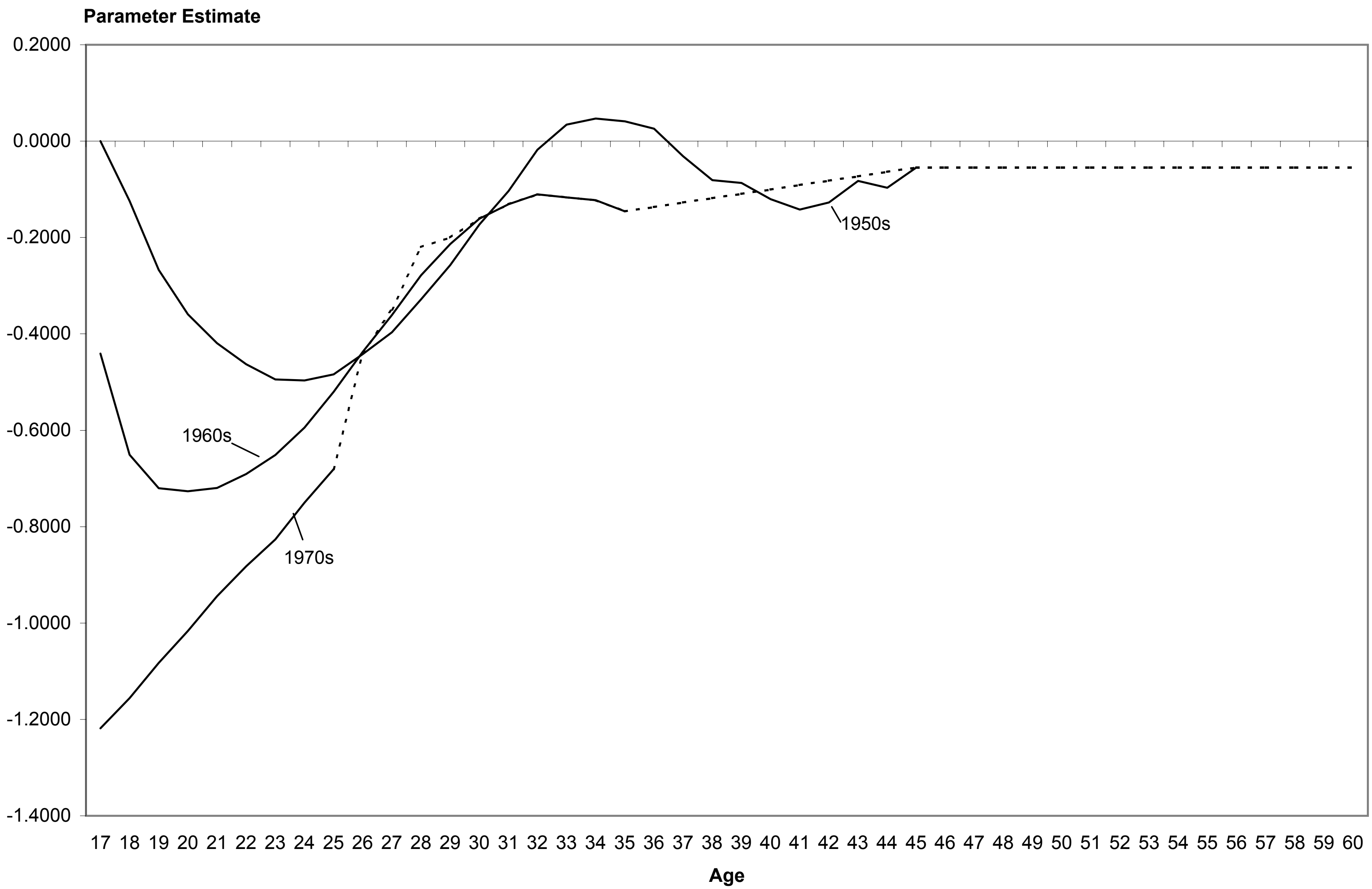


Figure 11: Residual Cohort Effects, Female Divorce

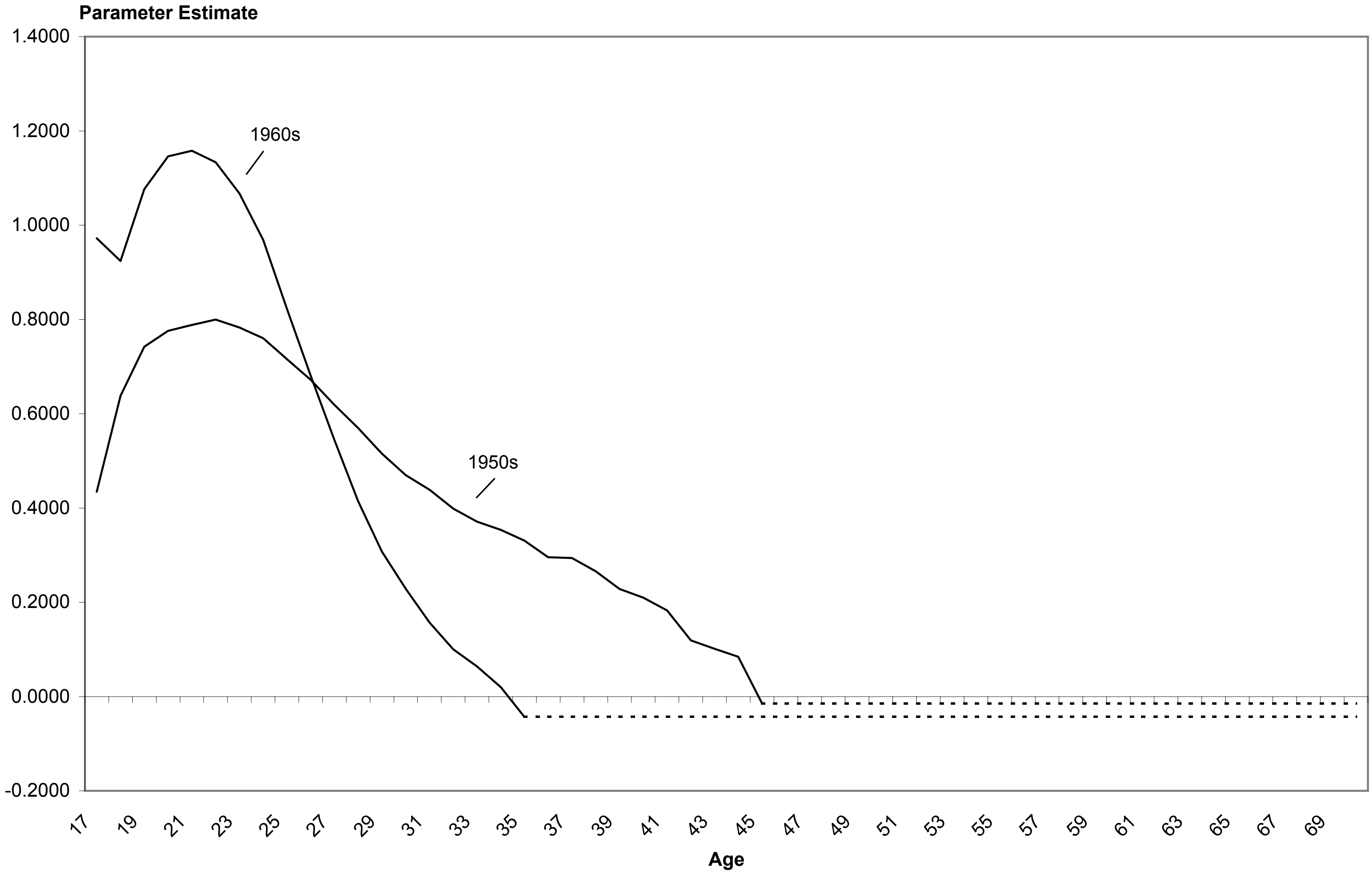


Figure 12: Residual Cohort Effects, Male Divorce

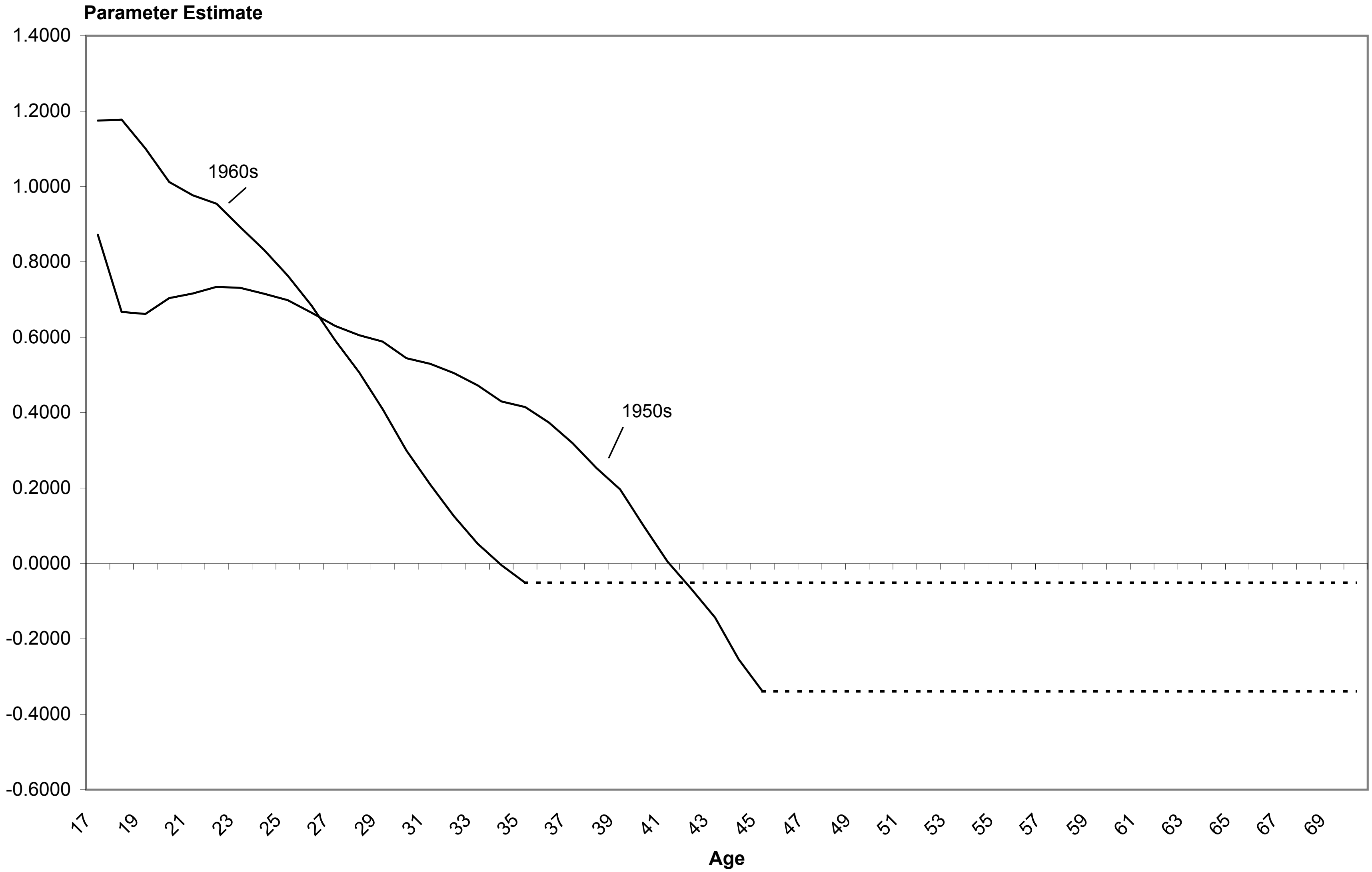


Figure 13: Residual Cohort Effects, Female Remarriage

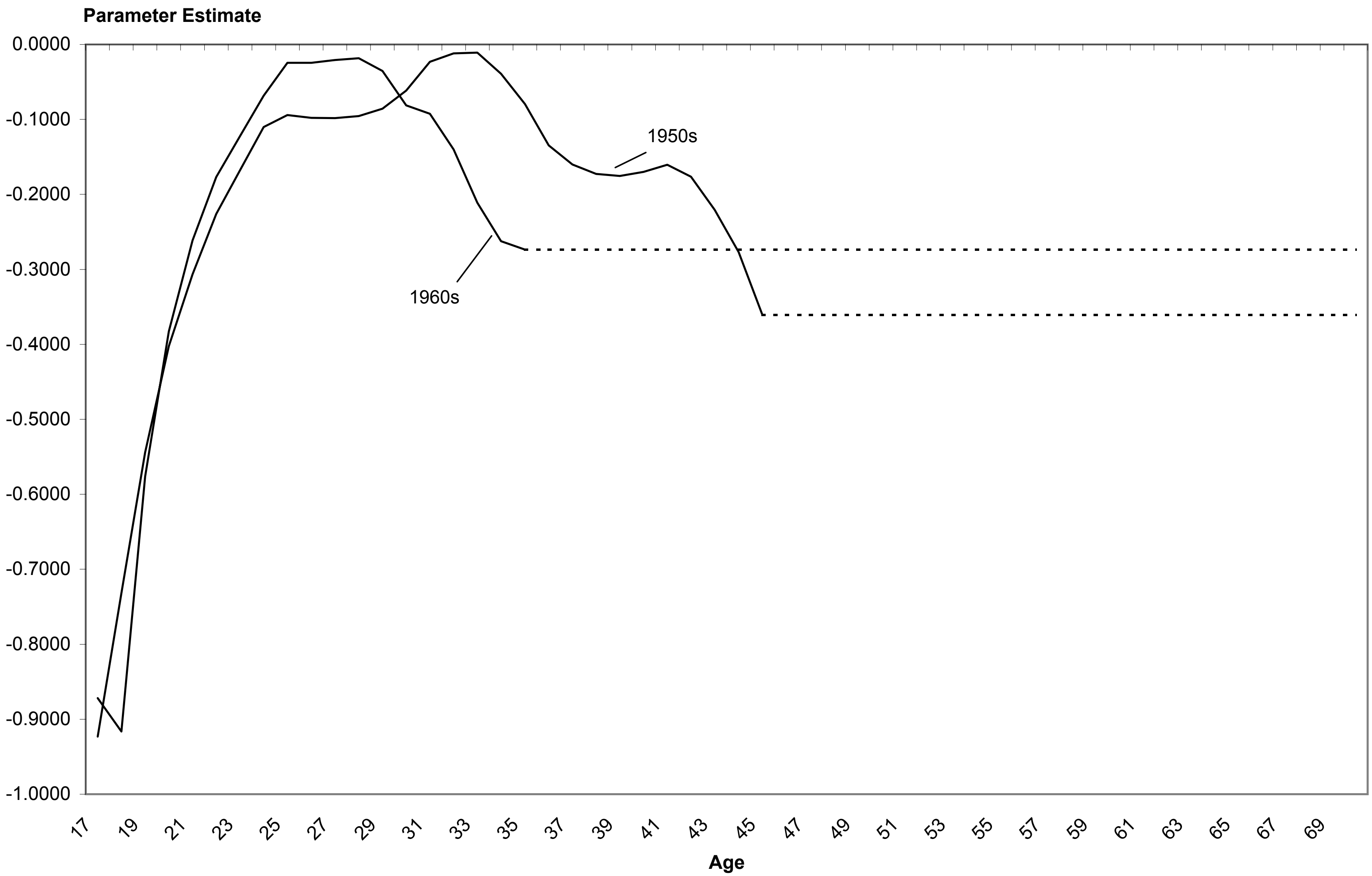


Figure 14: Residual Cohort Effects, Male Remarriage

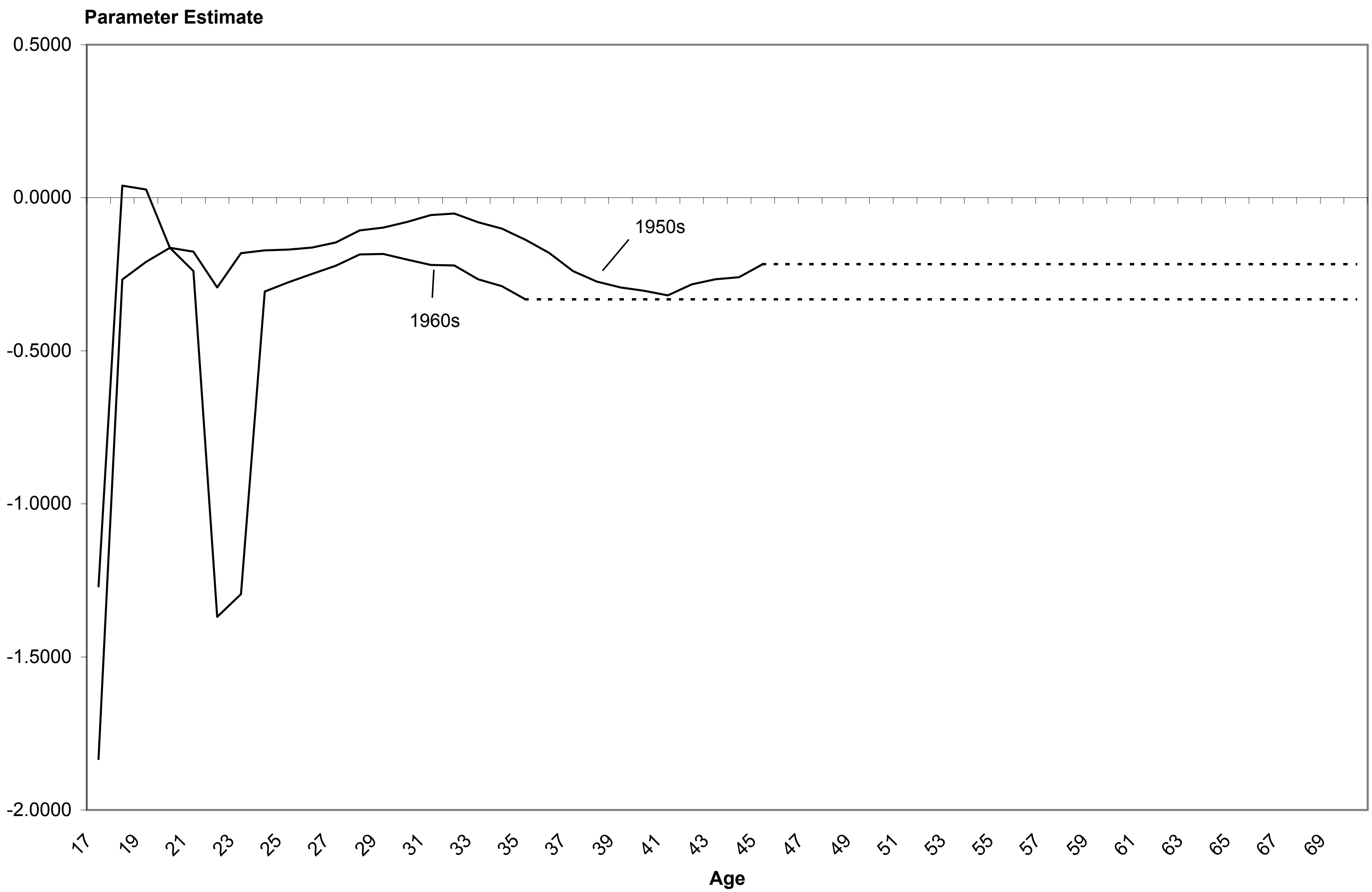


Table 8: Marital Status Distributions Over Time, by Sex and Year

	Social Security Administration (OCACT)				Congressional Budget Office Long-Term (CBOLT) Model			
	Never Married	Married	Divorced	Widowed	Never Married	Married	Divorced	Widowed
Overall Population								
2001	43%	44%	8%	5%	44%	44%	7%	6%
2025	41%	45%	9%	5%	42%	46%	6%	6%
2050	40%	45%	9%	6%	41%	46%	6%	7%
2075	40%	46%	9%	6%	40%	47%	6%	7%
Female Population								
2001	40%	43%	8%	8%	41%	43%	8%	9%
2025	38%	45%	10%	8%	38%	46%	7%	9%
2050	37%	45%	10%	9%	36%	47%	7%	10%
2075	36%	46%	10%	8%	35%	48%	7%	10%
Male Population								
2001	47%	45%	7%	2%	47%	45%	6%	3%
2025	45%	46%	7%	2%	46%	46%	5%	3%
2050	44%	46%	7%	3%	46%	45%	5%	4%
2075	43%	46%	7%	3%	45%	46%	5%	4%

Source: Authors' calculations based on SSA Area Population Projections 1941 to 2080, Office of the Chief Actuary.

Figure 15: Historical Simulation Calibration Factors, Females

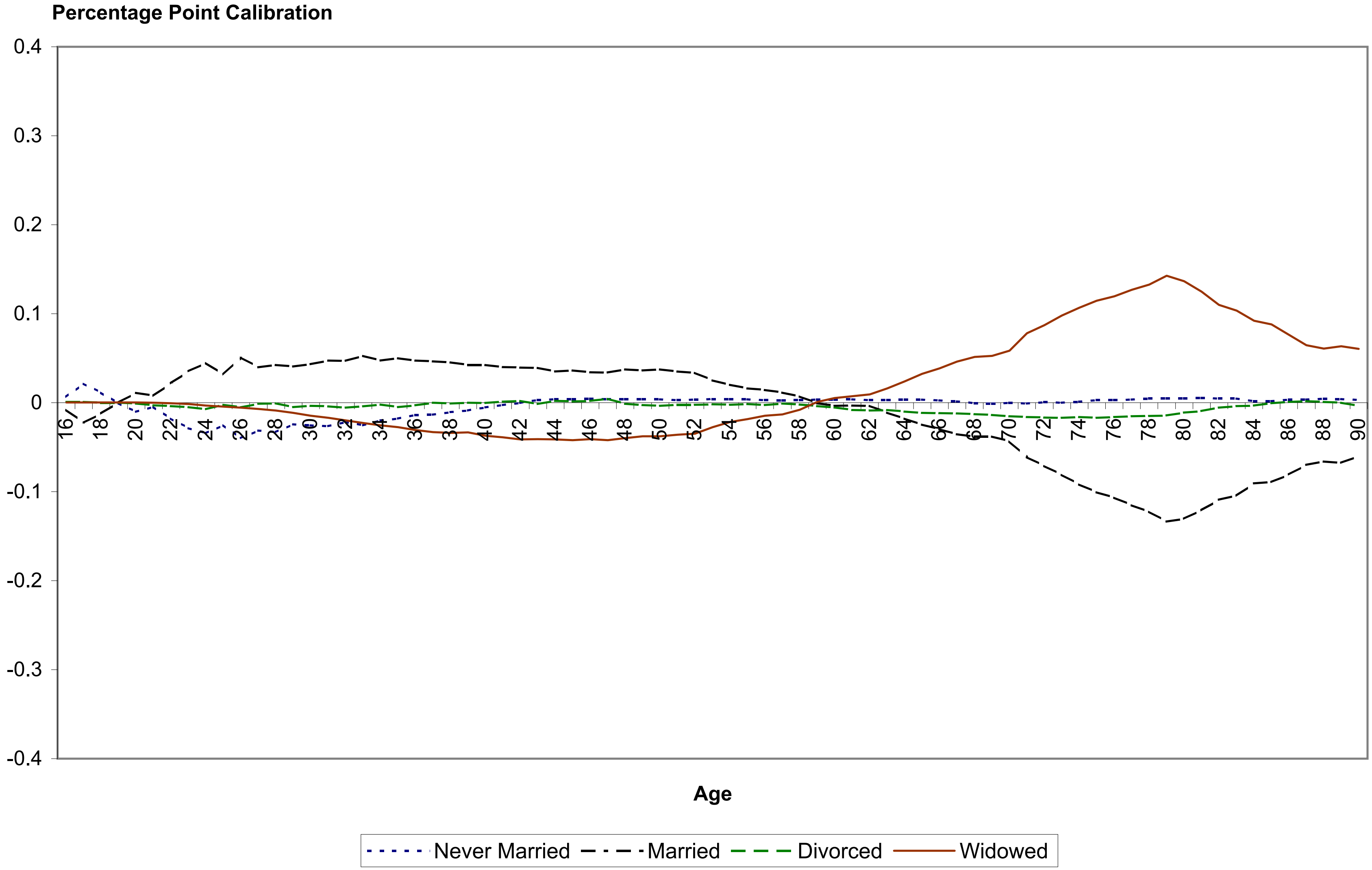


Figure 16: Historical Simulation Calibration Factors, Males

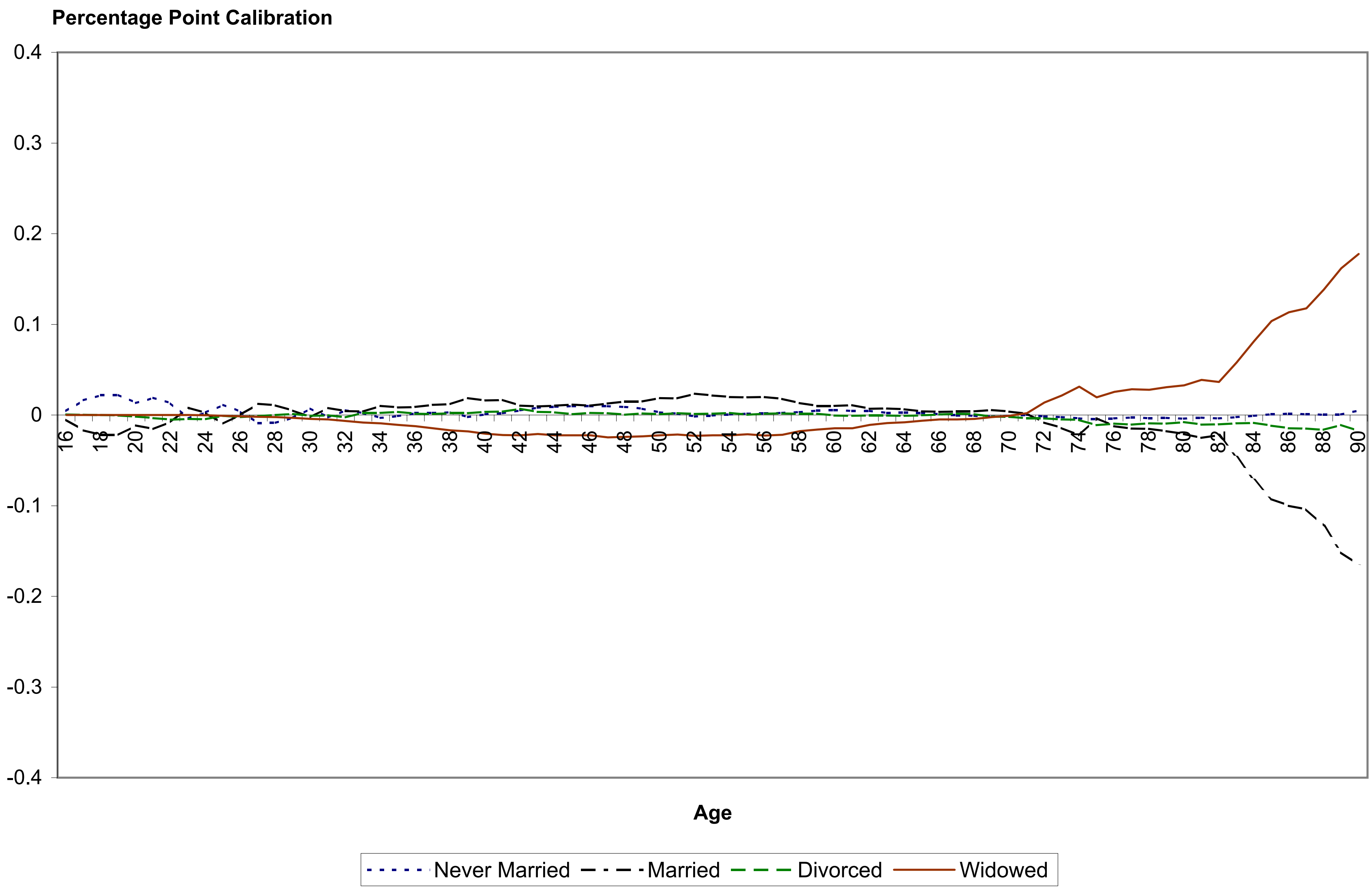


Figure 17: Marital Status for Females Ages 62-67, by Year

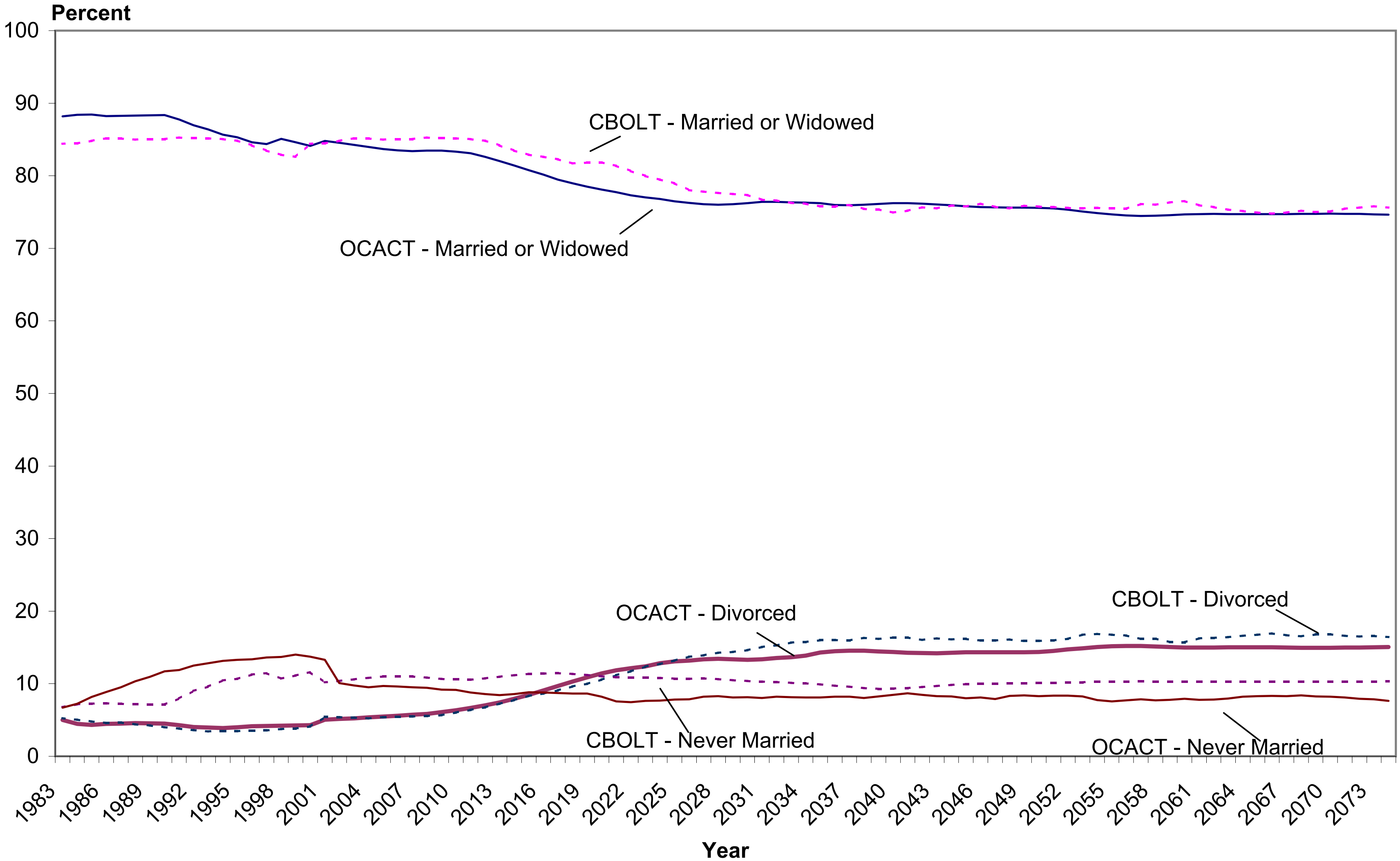


Figure 18: Marital Status for Males Ages 62-67, by Year

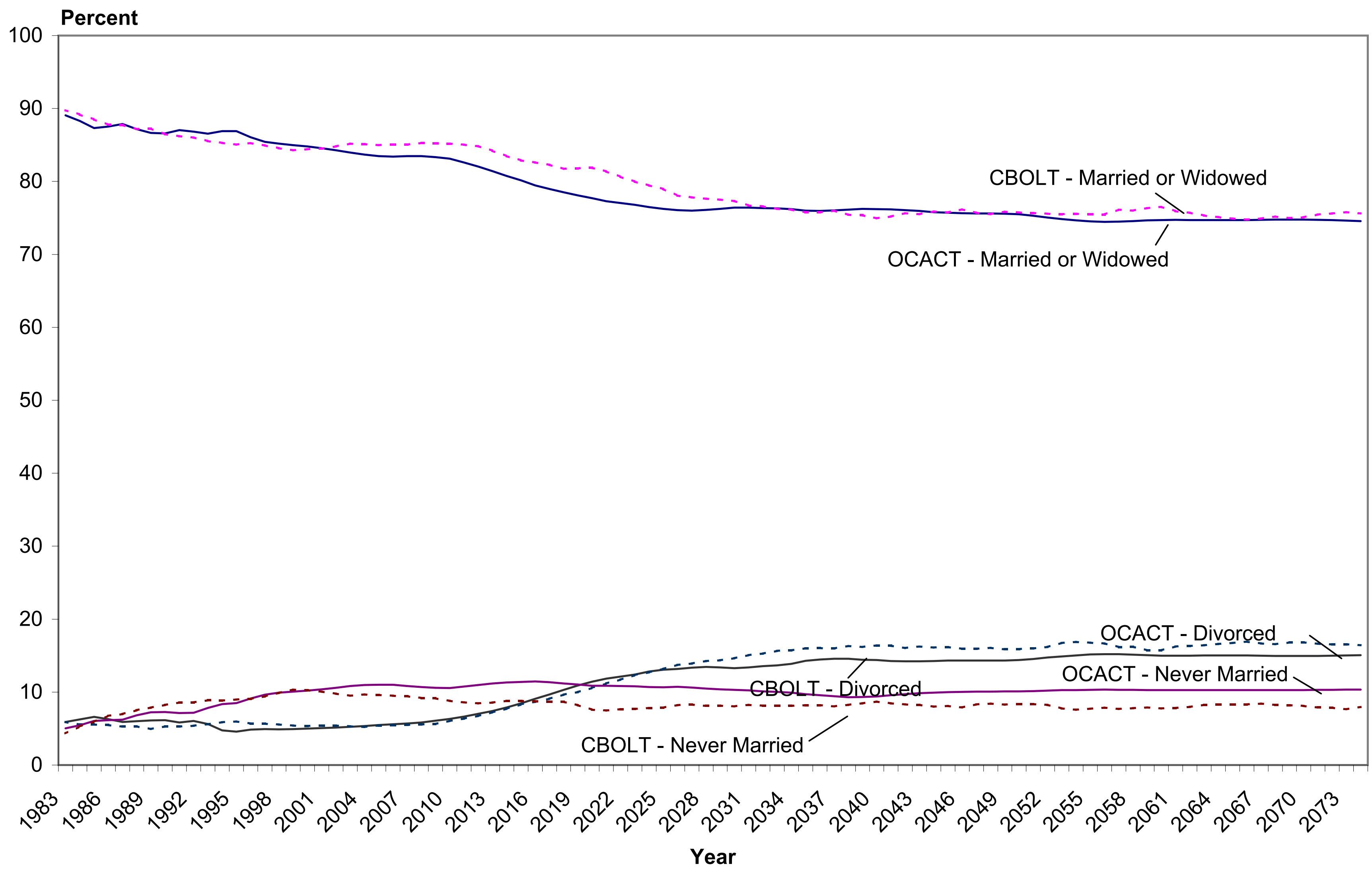


Figure 19: Mean Age At First Marriage

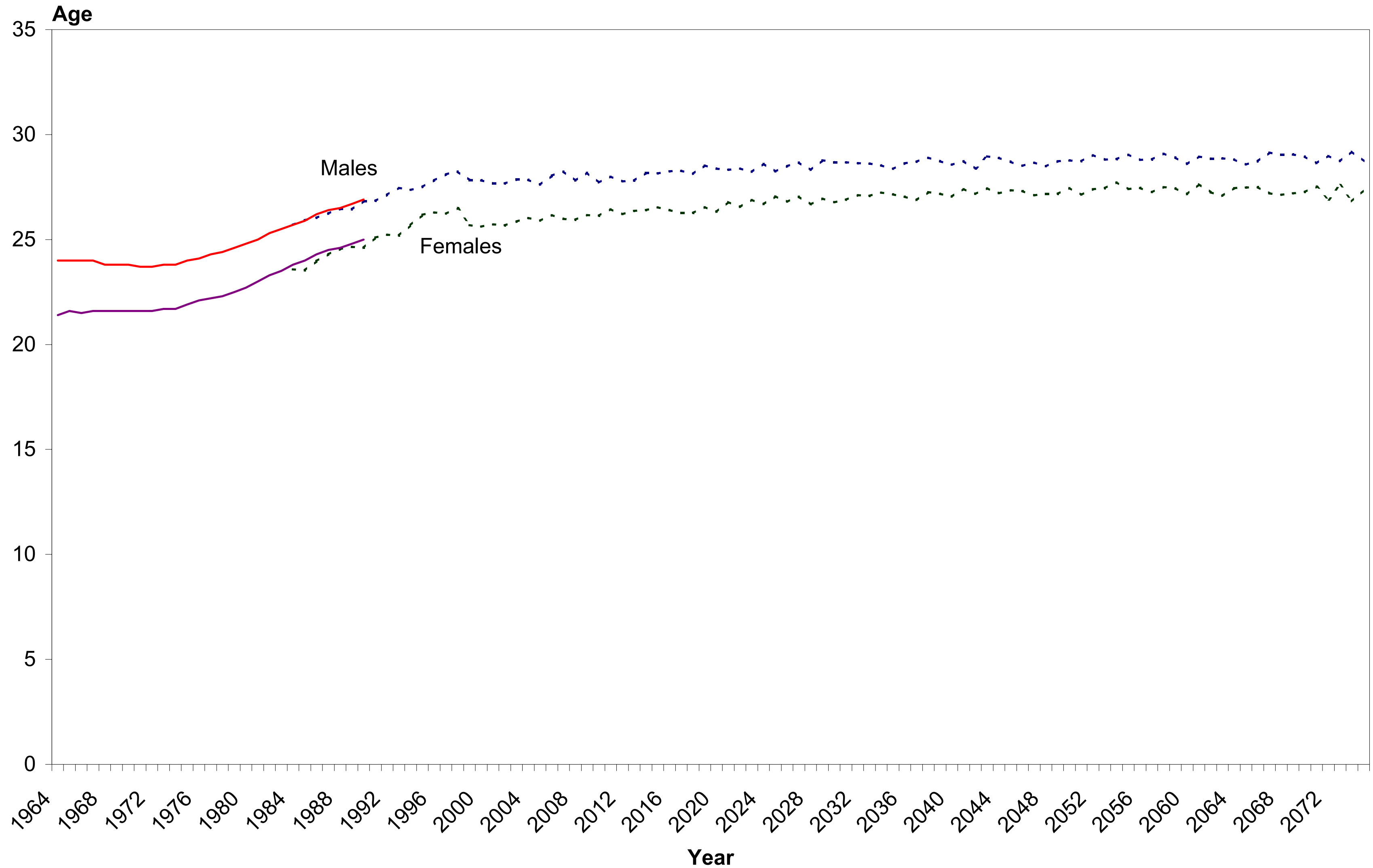


Table 9.
Distribution of Marital Durations at Time of Divorce,
by Number of Years Married

	0	1 to 4	5 to 9	10 to14	15 or More
NCHS - Actual					
1990	3%	32%	28%	15%	22%
Projected					
2005	9%	30%	24%	16%	23%
2015	8%	28%	24%	15%	27%
2025	6%	31%	27%	14%	23%
2035	6%	30%	25%	15%	24%
2045	7%	28%	28%	13%	25%
2055	6%	30%	25%	14%	23%
2065	8%	31%	22%	14%	26%
2075	7%	29%	26%	13%	26%

Table 10.
Percentage of Nonwidowed Women Ages 62-67 Eligible for OAI Spouse Benefits, by Lifetime Earnings Deciles

	Year							
	2005	**2015**	**2025**	**2035**	**2045**	**2055**	**2065**	**2075**
Earnings Decile								
1	95%	88%	88%	86%	83%	86%	85%	87%
2	95%	89%	87%	87%	82%	87%	88%	89%
3	90%	89%	85%	89%	84%	88%	89%	87%
4	90%	83%	83%	86%	83%	85%	85%	87%
5	86%	80%	83%	85%	79%	84%	85%	85%
6	88%	83%	83%	82%	80%	82%	84%	83%
7	80%	81%	82%	79%	74%	80%	83%	81%
8	84%	80%	77%	78%	74%	77%	78%	77%
9	81%	77%	75%	71%	69%	76%	77%	78%
10	77%	75%	72%	64%	65%	68%	70%	72%
All	87%	83%	81%	81%	77%	81%	82%	83%